Year: 2015

Remote sensing of soils

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Abstract: Global environmental changes are currently altering key ecosystem services that soils provide. Therefore, it is necessary to have up to date soil information on local, regional and global scales to monitor the state of soils and ensure that these ecosystem services continue to be provided. In this context, digital soil mapping (DSM) aims to provide and advance methods for data collection and analyses tailored towards detailed large-scale mapping and monitoring of soil properties. In particular, remote and proximal sensing methodologies hold considerable potential to facilitate soil mapping at larger temporal and spatial scales as feasible with conventional soil mapping methods [Mulder, 2013]. Existing remote and proximal sensing methods support three main components in DSM: (1) Remote sensing data support the segmentation of the landscape into homogeneous soil-landscape units whose soil composition can be determined by sampling. (2) Remote and proximal sensing methods allow for inference of soil properties using physically-based and empirical methods. (3) Remote sensing data supports spatial interpolation of sparsely sampled soil property data as a primary or secondary data source [Mulder, 2013]. Overall, remote and proximal sensed data are an important and essential source for DSM as they provide valuable data for soil mapping in a time and cost efficient manner. This document provides general insights into diverse aspects of soil related remote sensing, including DSM, remote sensing technologies and soil properties. In this context, we present the underlying concept of DSM and introduce approaches to predict the spatial distribution of soil properties. Furthermore, we introduce remote and proximal sensing technologies and the methodologies to extract soil properties in support of DSM. In this overview we consider established techniques within active, passive, optical and microwave remote sensing as well as proximal sensing that use key soil properties as proxies for soil conditions and characteristics. In addition, we discuss the opportunities, progress and limitations of remote and proximal sensing data in support of DSM and conclude by a gap analysis of current remote sensing technologies and products. Proximal sensing has been successfully used to derive quantitative and qualitative soil information [Viscarra Rossel et al., 2006b]. Most reported studies revealed the high potential of proximal sensing to estimate soil properties based on clear absorption features at the laboratory and local scale [Ben-Dor et al., 2008]. However, for large-scale mapping of soil properties, methods need to be extended beyond the plot scale. Important qualitative and, to a lesser extent, quantitative soil information can be obtained from remote sensing data. Airborne and spaceborne remote sensing provides qualitative information on soil properties having clear diagnostic absorption features at a regional to global scale. However, remote sensing-derived information has a lower accuracy and feasibility to obtain information compared to proximal sensing. The main limiting factors are (1) the coarse spatial and spectral resolution, (2) the low signal-to-noise ratio of high-resolution remote sensing data and (3) the bands of multispectral satellite sensors have not been positioned at diagnostic wavelengths. Future improvement to detect soil properties on a regional to global scale with high accuracy can be expected from recently launched Sentinel-1 and upcoming Sentinel-2, SWAP, and EnMAP missions. Despite the large potential of using proximal and remote sensing methods in support of DSM, advances are necessary to fully develop large-scale methodologies and soil products. Currently, DSM-studies make limited use of existing analysis and geostatistical methods to exploit the full potential of proximal and remote sensing data [Ben-Dor et al., 2009; Dewitte et al., 2012]. Improvements may be expected in the fields of developing more quantitative methods, enhanced geostatistical analysis that allow working with large remote sensing datasets. Further research priorities involve the development of operational tools to quantify soil properties, multiple sensor integration, spatiotemporal modelling and

improved transferability of soil mapping approaches to other landscapes. This will allow us in the near future to deliver more accurate and comprehensive information about soils, soil resources and ecosystem services provided by soils at regional and, ultimately, global scale.

Remote Sensing of Soils

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V.L. Mulder has received the support of the European Union, in the framework of the Marie-Curie FP7 COFUND People Programme, through the award of an AgreenSkills' fellowship (under grant agreement n° 267196).

Released by:

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Version:

Final Version 5.2
Zurich, 31.10.2014

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Summary

Global environmental changes are currently altering key ecosystem services that soils provide. Therefore, it is necessary to have up to date soil information on local, regional and global scales to monitor the state of soils and ensure that these ecosystem services continue to be provided. In this context, digital soil mapping (DSM) aims to provide and advance methods for data collection and analyses tailored towards detailed large-scale mapping and monitoring of soil properties. In particular, remote and proximal sensing methodologies hold considerable potential to facilitate soil mapping at larger temporal and spatial scales as feasible with conventional soil mapping methods [*Mulder*, 2013]. Existing remote and proximal sensing methods support three main components in DSM: (1) Remote sensing data support the segmentation of the landscape into homogeneous soil-landscape units whose soil composition can be determined by sampling. (2) Remote and proximal sensing methods allow for inference of soil properties using physically-based and empirical methods. (3) Remote sensing data supports spatial interpolation of sparsely sampled soil property data as a primary or secondary data source [*Mulder*, 2013]. Overall, remote and proximal sensed data are an important and essential source for DSM as they provide valuable data for soil mapping in a time and cost efficient manner.

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Proximal sensing has been successfully used to derive quantitative and qualitative soil information [*Viscarra Rossel et al.*, 2006b]. Most reported studies revealed the high potential of proximal sensing to estimate soil properties based on clear absorption features at the laboratory and local scale [*Ben-Dor et al.*, 2008]. However, for large-scale mapping of soil properties, methods need to be extended beyond the plot scale. Important qualitative and, to a lesser extent, quantitative soil information can be obtained from remote sensing data. Airborne and spaceborne remote sensing provides qualitative information on soil properties having clear diagnostic absorption features at a regional to global scale. However, remote sensing-derived information has a lower accuracy and feasibility to obtain information compared to proximal sensing. The main limiting factors are (1) the coarse spatial and spectral resolution, (2) the low signal-to-noise ratio of high-resolution remote sensing data and (3) the bands of multispectral satellite sensors have not been positioned at diagnostic wavelengths. Future improvement to detect soil properties on a regional to global scale with

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Despite the large potential of using proximal and remote sensing methods in support of DSM, advances are necessary to fully develop large-scale methodologies and soil products. Currently, DSM-studies make limited use of existing analysis and geostatistical methods to exploit the full potential of proximal and remote sensing data [*Ben-Dor et al.*, 2009; *Dewitte et al.*, 2012]. Improvements may be expected in the fields of developing more quantitative methods, enhanced geostatistical analysis that allow working with large remote sensing datasets. Further research priorities involve the development of operational tools to quantify soil properties, multiple sensor integration, spatiotemporal modelling and improved transferability of soil mapping approaches to other landscapes. This will allow us in the near future to deliver more accurate and comprehensive information about soils, soil resources and ecosystem services provided by soils at regional and, ultimately, global scale.

Content

Abbreviations and Definitions

Abbreviation	Description
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
BRDF	Bidirectional reflectance distribution function
CEC	Cation Exchange Capacity
DEM	Digital Elevation Model
DSM	Digital Soil Mapping
DTM	Digital Terrain Model (including vegetation heights)
EM	Electromagnetic spectrum
FIR	Far infrared
GIS	Geographic Information System
GPR	Ground Penetrating Radar
GPS	Global Positioning System
MESMA	Multiple Endmember Spectral Mixture Analysis
MLR	Multiple Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
NABODAT	Swiss National Soil Information System
PLSR	Partial Least Square Regression
PFT	Plant Functional Types
PS	Proximal Sensing
RS	Remote Sensing
SAM	Spectral Angle Mapper
SAR	Synthetic Aperture Radar
SMAP	Soil Moisture Active Passive (NASA satellite)
SMOS	Soil Moisture Ocean Salinity (ESA Earth Explorer Satellite)
SOC	Soil Organic Carbon
SWI	Soil Water Index
SWIR	Shortwave infrared
TIR	Thermal infrared
VNIR	Visible and near infrared

Term	Definition
CLORPT / SCORPAN	Mnemonics for empirical quantitative descriptions of relationships between soil and environmental factors in adaptation of Hans Jenny's five factors of soil formation. These relations are used as soil spatial prediction functions for the purpose of Digital soil mapping.
Diffuse Reflectance Spectroscopy	A non-invasive technique that measures the characteristic reflectance spectrum produced as light passed through a medium. This spectrum

	contains information about the optical properties and structure of the medium being measured.
Digital Elevation Model	Digital Elevation Models is a digital model or 3D representation of a terrain's surface. The term digital surface model represents the earth's surface and includes all objects, whereas the digital terrain model represents the bare ground surface without any objects like plants and buildings.
Digital Soil Mapping	The creation and population of spatial soil information by the use of field and laboratory observational methods coupled with spatial and non-spatial soil inference systems.
Ellenberg indicators	The Ellenberg indicator values scale the flora of a region along gradients reflecting light, temperature, moisture, soil pH, fertility and salinity gradients. This way, the flora can be used to monitor environmental change and thereby changes in the soil.
Imaging Spectrometry	Imaging spectroscopy, also known as hyperspectral imaging, is defined as a passive remote sensing technology that is acquiring simultaneous images in many spectrally contiguous, registered bands such that for each pixel a reflectance spectrum can be derived.
Landsat	NASA Earth Observation Satellite Programme
Magnetic susceptibility	Method to analyse the occurrence and distribution of occurrence of ferromagnetic minerals (e.g., magnetite, greigite) in soils
Multispectral Imaging	Acquiring image data at several discrete, discontinuous regions across the visible and infrared electromagnetic spectrum.
Plant Functional Types	A system commonly used by climatologists and biologists to classify plants according to their physical, phylogenetic and phenological characteristics as part of an overall effort to develop a vegetation model for use in land use studies and climate models.
Proximal Sensing	Remotely sensed measurements that are taken at the field or laboratory level.
Remote Sensing	Process of inferring information from distant measurements of the upwelling emitted or reflected electromagnetic radiation, typically from satellite or airborne platforms.
Revisit Time	Time between two satellite image acquisitions for a given location
Sentinel	Earth Observation satellite missions that are integral part of the European Copernicus Programme
Spectral Unmixing	Spectral unmixing decomposes a source spectrum into a set of given known spectra, or endmember spectra, to determine the relative abundance of materials depicted in multi- or hyperspectral imagery.

1 Introduction

1.1 Motivation on remote sensing of soils

Over the past decades, the Earth's surface has witnessed major changes in land use and land cover. These changes are likely to continue, driven by demographic pressure and by climate change. As part of the Earth's spheres, the pedosphere is responding and contributing to these environmental changes [*Macías and Arbestain*, 2010]. Observed changes in the functioning of the pedosphere renewed the recognition that soil resources provide key ecosystem services and play a fundamental role for assuring food security [*GlobalSoilPartnership*, 2011; *Grunwald*, 2011; *Mulder*, 2013]. In this context, monitoring tools are needed for maintaining a sustainable ecological status and improving soil conservation. The implementation of sustainable agricultural, hydrological, and environmental management requires an improved understanding of the soil, at increasingly higher resolutions. Information on spatial and temporal variations in soil properties are required for use in conservations efforts, climate and ecosystem modelling, as well as engineering, agricultural, forestry applications, erosion and runoff simulations [*King et al.*, 2005]; Soils are a vital natural resource that provide multiple ecosystem services. Conventional soil sampling and laboratory analyses cannot efficiently provide the needed information, because these analyses are generally time consuming, costly, and limited in retrieving the temporal and spatial variability. In this context, remote sensing (RS) is now in a strong position to provide meaningful spatial data for studying soil properties on various spatial scales using different parts of the electromagnetic spectrum.

1.2 Scope and structure of this document

This document provides general insights into diverse aspects of soil related RS and PS, including of DSM. Key abbreviations and definitions of terms can be found in beginning of this document. In Chapter 2, we introduce key principles of DSM, explain basic concepts of RS and PS technologies and present an overview of remote sensing based soil products. In this context, we consider established techniques within active, passive, optical and microwave RS and PS that infer key soil properties, as well as proxies for soil conditions and characteristics. For a comprehensive review, Chapter 3 provides in-depth information on remote sensing of soils and builds upon the issues and topics presented in Chapter 2. Here, we review in particular DSM approaches, remote sensing technologies and related soil products. Furthermore, we emphasize in Chapter 4 on remote sensing opportunities and limitations, with respect to DSM and soil products. We conclude the discussion of technological constraints and potentials by outlining future trends and challenges for soil mapping using digital approaches. In Chapter 5, we summarize and highlight the use of remote and proximal sensing for soil survey, based on the main conclusions and recommendations. Furthermore, we provide next to the in-text references (Chapter 6) an overview of the key literature on remote sensing of soil (Chapter 7), as a guideline for further reading. Finally, we highlight some digital resources in Chapter 8, to which we referred previously or might be of general interest to the reader.

2 Overview on remote sensing of soils

2.1 Digital soil mapping

The advent of new technologies along with vast amounts of data and the need for effective soil characterization led to digital soil mapping (DSM). Digital soil mapping is defined as: 'the creation and population of spatial soil information by the use of field and laboratory observational methods coupled with spatial and non-spatial soil inference systems [*Lagacherie et al.*, 2007; *McBratney et al.*, 2003]' [*Carré et al.*, 2007]. DSM relies on quantitative methods to integrate diverse soil observations from field, laboratory and remote sensing and proximal sensing data [*Grunwald*, 2010] for inferring spatial patterns of soils across various spatial and temporal scales. Using a broad range of data sources and methods, DSM aims to provide up-to-date and accurate soil maps to meet the current and future need for soil information [*Mulder*, 2013] (Fig. 1).

New tools in the field of statistics and spawned new areas, such as data mining and machine learning have been exploited [*Hastie et al.*, 2009], to take advantage of large soil and environmental data stores for improved soil data and information. In addition, the increasing power of tools such as Geographic Information Systems (GIS), Global Positioning System (GPS), remote and proximal sensors (RS and PS) and data sources such as those provided by digital elevation models (DEM) increased the potential of mapping soils over vast areas. Consequently, worldwide, organizations are investigating the possibility of applying the new information technology and science to assess soil properties, resources and class maps. This recent approach of soil surveying combines limited field and laboratory observations with the vast amount of RS data using GIS and advanced quantitative predictive models for DSM [*McBratney et al.*, 2003]. For further details on DSM see section 3.1 and 4.3.

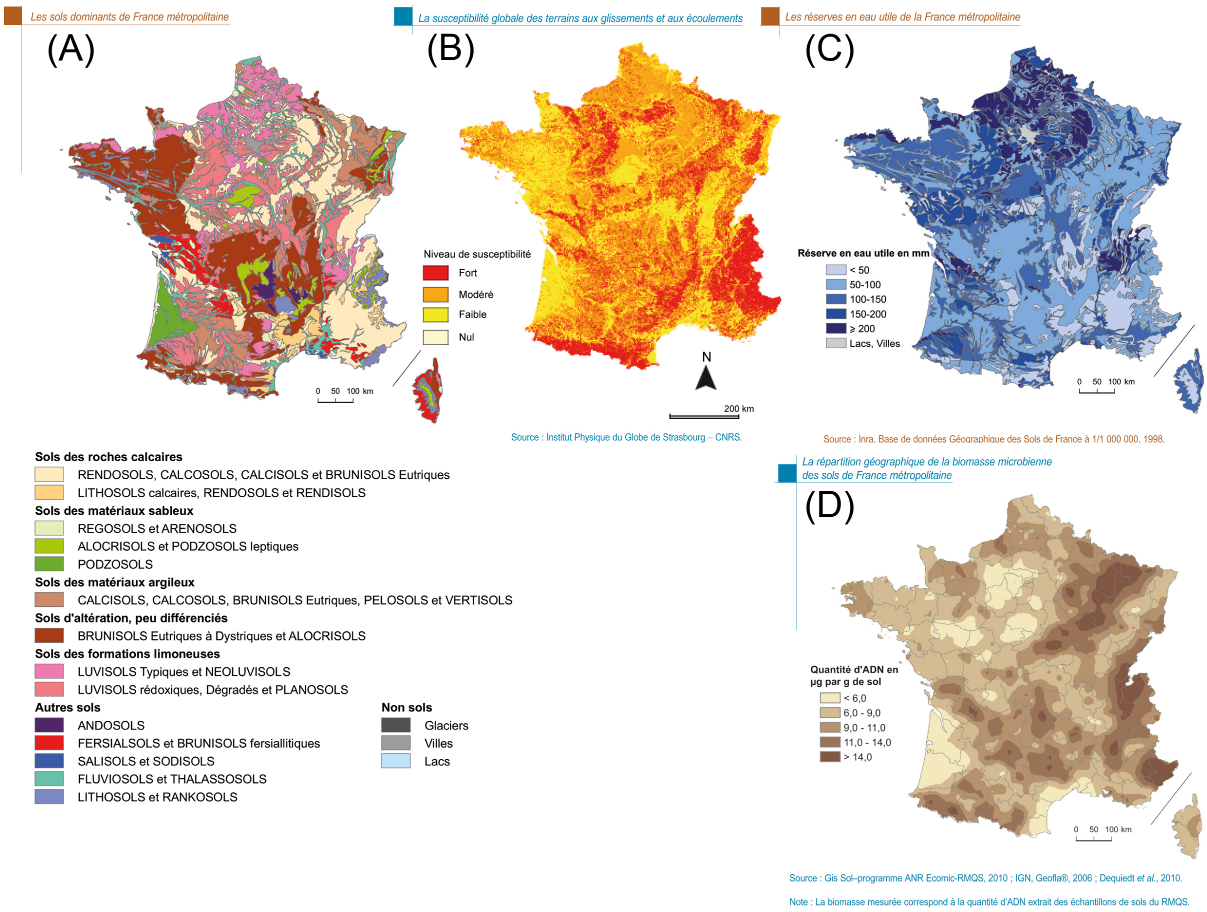

Fig. 1. Compilation of a classical soil map (A) and Digital Soil Maps (B, C, D) characterizing soil susceptibility to landslides and runoff (B), water reserves (C) and microbial biomass (D) of soils in France [*GisSol*, 2011].

2.2 Remote sensing technologies

Remote sensing (RS) is the process of inferring surface parameters from distant measurements of the upwelling emitted or reflected electromagnetic radiation from the land surface. The radiation reflected or emitted by soil varies according to a range of chemical and physical characteristics of the soil matrix [*Anderson and Croft*, 2009; *Barnes et al.*, 2003; *Mulder et al.*, 2011; *Schmugge et al.*, 2002]. Therefore, it is possible to discriminate between different soil surfaces and to infer soil properties based on the measured radiation [*Dewitte et al.*, 2012].

In this document, we use the term "remote sensing" (RS) for airborne and spaceborne acquisitions, whereas "proximal sensing" (PS) refers to ground-based laboratory and field measurements. Soil PS generally measures soil surface properties in a high spatial and spectral resolution from a short-range. Depending on the source of energy utilized in the data acquisition, RS sensors may be classified as being active or passive. Active sensors produce their own energy for sensing objects, whereas the passive satellite sensors depend on external energy sources (e.g., sun or earth).

There are various RS systems, operating in various portions of the electromagnetic spectrum, which are suitable for soil spectroscopy. Most passive systems operate in the visible, near-infrared (VNIR), shortwave infrared (SWIR), thermal infrared (TIR), and microwave portions of the electromagnetic (EM) spectrum, such as multispectral instruments and imaging spectrometers. The majority of active sensors operate in the microwave portion of the EM spectrum. Here, wavelengths are unaffected by typical meteorological conditions, making it the sensor of choice when continuity of data must be ensured.

In comparison to ground-based sensors, air- and space born sensors have larger ground coverage. RADAR and passive microwave systems have, until recently, only been capable of providing data for regional- or catchment-scale assessment of soil properties. Airborne systems (LiDAR, multi-spectral and hyperspectral) have demonstrated capabilities for monitoring at finer spatial resolutions and over smaller extents, including identifying key variables relevant to soil science (e.g., mineralogy, moisture and elevation). At the finest spatial scale, PS techniques, such as laboratory laser profiling, already demonstrated their application for assessment of various soil parameters [*Jester and Klik*, 2005].

In addition, moderate and coarse resolution sensors provide more frequent coverage than high-resolution sensors, such as the *Landsat, ASTER* and *SPOT* sensors. The higher frequency helps to assess (1) daily or weekly variation in surface conditions, (2) improves the methods for the delineation of soil units and the estimation of soil properties and (3) the assessment of soil threats such as soil erosion by water and by wind and landslides.

The advantages of RS for non-destructive spatial assessment of soils have been recognized since the 1920s, when aerial photos where used to map boundaries of different soil series [*Bushnell*, 1932]. Over the last decades, a high number of sensors have been applied to improve the retrieval of direct and indirect soil parameters because of the high potential of RS to retrieve soil surface parameters. The operational RS systems (passive and active) and analysis techniques for estimating of soil parameters include various sensors (see section 3.2). For passive remote sensing, we can consider four principal types of sensors:

(i) Optical multispectral sensors, particularly adapted for land use and mineralogical analysis.
(ii) Optical imaging spectroscopy sensors, particularly adapted for deriving soil properties (e.g. mineralogical composition, iron oxides and organic matter).
(iii) Optical TIR sensors, particularly adapted for soil temperature estimation.
(iv) Passive microwave sensors, particularly adapted to soil moisture estimation.

Active remote sensing holds considerable potential for characterizing soil moisture, roughness, and texture. Here, we distinguish between RADAR and LiDAR sensors:

(i) Synthetic aperture radar (SAR) sensors, particularly adapted for soil moisture, texture and salinity estimations.
(ii) Radar scatterometer sensors, adapted for soil moisture estimates.
(iii) LiDAR sensors, particularly adapted for terrain analysis.

For the interpretation of RS data, one should be aware of general limitations related to RS observations and specific disadvantages related to the inference of soil information; in general, there is a trade-off between spatial and temporal resolution of space and airborne observations. Revisit times of polar orbiting satellites generally vary from days to weeks, depending on the satellite orbital and energy constraints, its observation geometry and downlink capacity. The spatial resolution depends on both the energy level of the measured radiation and the observation distance. Whereas spaceborne passive microwave sensors inherit spatial resolutions on the order of tens of kilometres, optical airborne observations range within the cm to meter scale. Furthermore, RS data requires corrections accounting for atmospheric, geometric, radiometric and topographic effects. For example, in rugged terrain, the observational geometry in combination with high topography may limit continuous assessment of the earth surface.

Specifically for soil RS, soil coverage by vegetation and lichens are hampering investigations by optical sensors. In such cases, spectral signatures of land cover other than soils (e.g. vegetation, urban areas, roads and water surfaces) need to be masked, resulting in incomplete coverage of the study area. Furthermore, the majority of RS systems only characterize the surface or, in optimum conditions, shallow depths of soils. These surface characteristics may not be representative for the deeper soil profile. Still, RS-derived observations of the soil surface, soil surface variations, and partially obscured soil surfaces can be used to infer soil properties. Beside the direct retrieval of soil attributes, proxies may represent an alternative; stratification using indicator species of vegetation for specific habitats enables soil types to be allocated to specific strata, and vice versa [*Mücher et al.*, 2009]. However, the success of the latter method is limited to the availability of data for potential natural vegetation or indicator species, and is hampered in ecoregions significantly altered by humans. For further details on remote sensing technologies, see section 3.2 and 4.1.

2.3 Remote sensing products

RS offers possibilities for extending existing soil survey data sets and can be used in various ways. Firstly, it may help segmenting the landscape into internally more or less homogeneous soil–landscape units for which soil composition can be assessed by sampling using classical or more advanced methods (Fig. 2). Automated spatial segmentation of the landscape supporting soil–landscape mapping is typically based on first- and second-order derivatives of DEMs, observed parent material and spatiotemporal vegetation changes. In this context, spatial and temporal changes of vegetation indices and biogeographical gradients have been used to improve spatial segmentation [*Mulder*, 2013]. Secondly, RS data can be analysed using physically-based or empirical methods to derive soil properties. Moreover, RS can be used as a data source supporting DSM [*Ben-Dor et al.*, 2008; *Slaymaker*, 2001]. Finally, RS facilitate mapping inaccessible areas by reducing the need for extensive time-consuming and costly field surveys [*Mulder*, 2013; *Mulder et al.*, 2011].

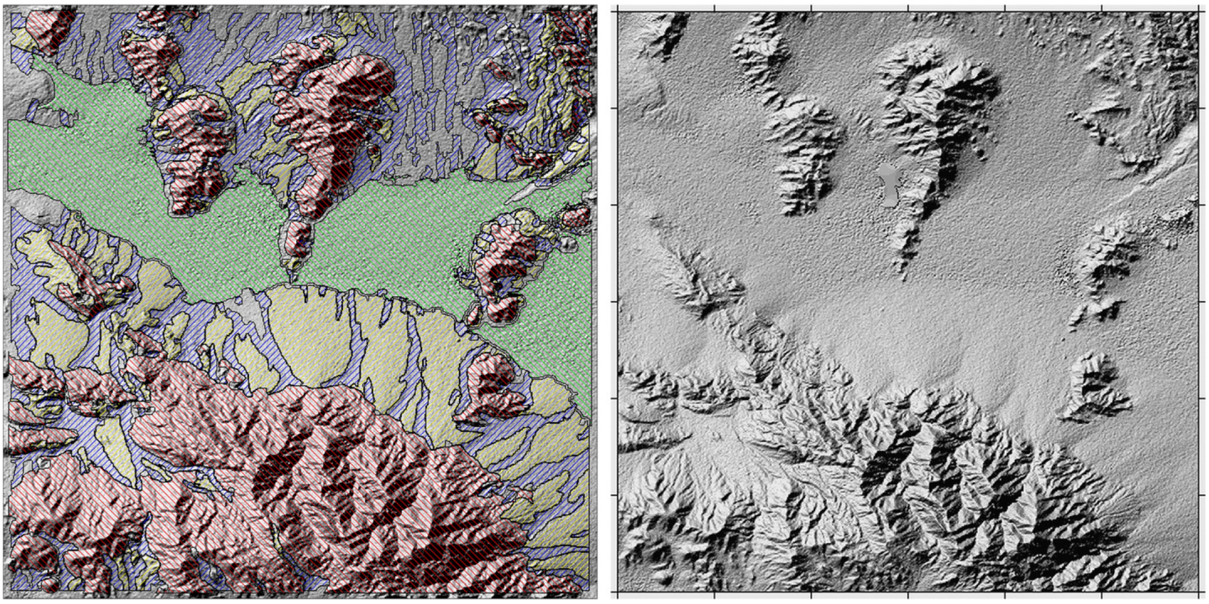

Fig. 2. (Left) Landform delineations: red hatch: mountains, yellow hatch: alluvial fans, green hatch: valleys, blue hatch: wash drainage areas, unshaded: unclassified areas. (Right) the corresponding shaded relief: 4x vertical exaggeration [*Leighty*, 2004].

RS-derived soil and environmental variables are widely used in DSM. PS has been employed in the VNIR and SWIR for inferring a multitude of soil properties, with varying success [*Reeves*, 2010], including soil texture, organic matter, pH and iron content. Other soil sensors map penetration resistance, apparent electrical conductivity, or magnetic susceptibility [*Viscarra Rossel et al.*, 2011].

Recently, major advancements in the spatial assessment of soil properties have emerged, predominantly from optical and microwave remote sensing, next to large-scale DSM-projects devoted to a Global Soil Observing System (e.g. e-SOTER, S-World). Summarizing, RS studies address particularly the following soil parameters:

(i) *Mineralogy*: mineralogical composition of soils indicating its host rock and soil fertility.
(ii) *Soil texture*: indicating the sand/silt/clay content (i.e. soil grain sizes), which influences physical, chemical, and biological soil processes.
(iii) *Soil moisture*: indicating the volumetric soil water content, a key parameter influencing a range of hydrological processes at a variety of spatiotemporal scales, including runoff, erosion and solute transport. Soil moisture information is furthermore important for managing agricultural irrigation.
(iv) *Soil organic carbon*: biomass and non-biomass sources that improve various physical properties of soils, such as cation exchange capacity (CEC), water-holding capacity and nutrient content, among others.
(v) *Iron content*: indicator of soil fertility and the age of the sediments.

(vi) *Soil salinity*: indicating the salt content in soils that may increase driven by natural processes such as mineral weathering, water table variations or artificial processes such as fertilization or land clearing.

(vii) *Carbonates*: originating from calcite-rich parent material, influencing the soil alkalinity (high soil pH) and structure with potential negative effects on water infiltration and plant growth. The soil pH specifically affects plant nutrient availability by controlling the chemical forms of the nutrient.

(viii) *Soil degradation and contamination*: the decline in soil quality caused by its improper use, including agricultural, pastoral, industrial or urban purposes. Over time, this may result in the loss of organic matter, decline in soil fertility, decline in structural conditions, erosion, contamination by toxic chemicals or pollutants and other adverse changes (Fig. 3).

For further details on remote sensing products see section 3.3 and 4.2.

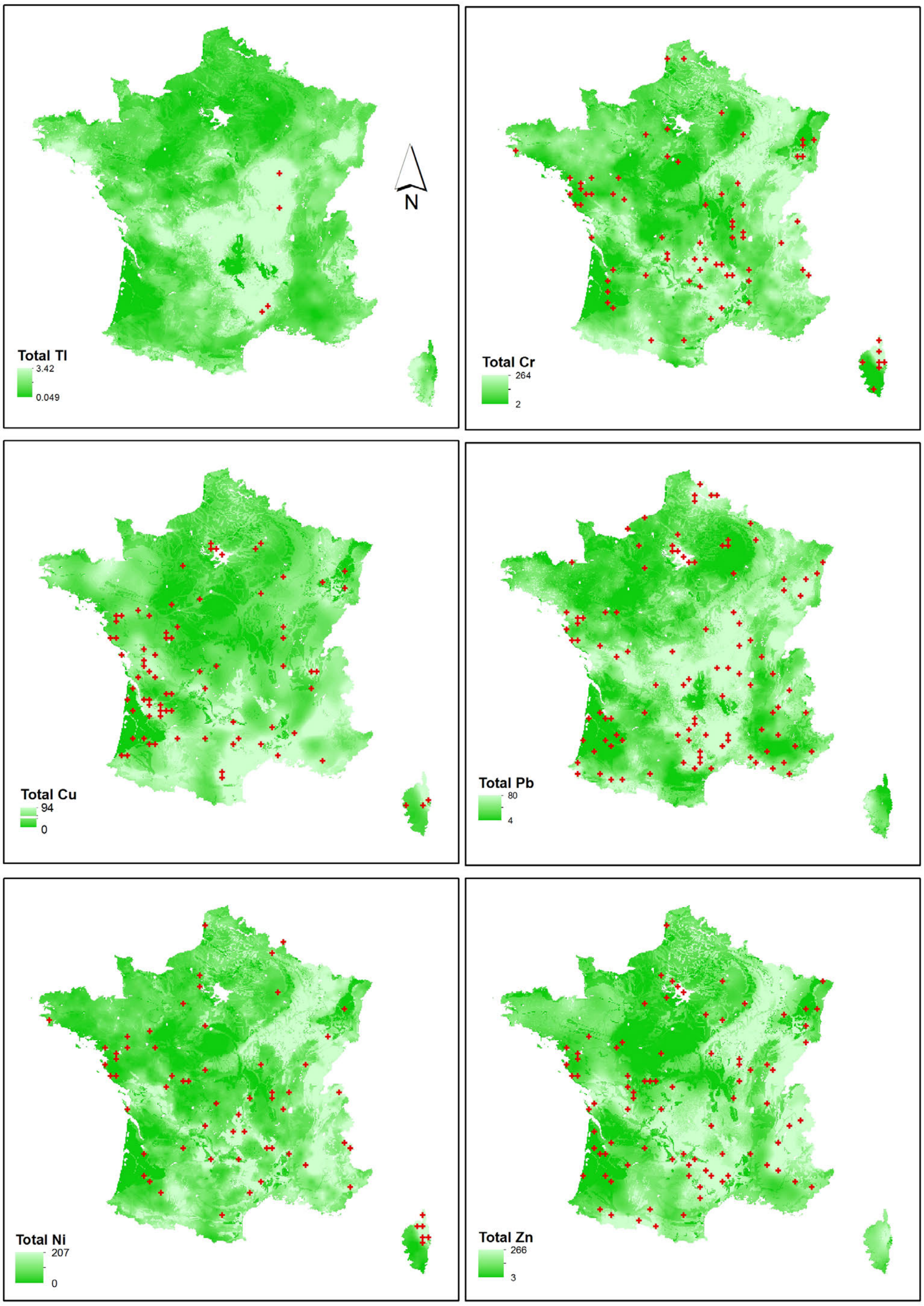

Fig. 3. Robust regression kriging prediction of trace elements across France, excluding the effect of short-scale processes; Red crosses represent the location of outliers [after *Saby et al.*, 2011].

3 In-depth review on remote sensing of soils

3.1 Digital soil mapping

3.1.1 Concept of digital soil mapping

DSM relies on field and laboratory soil observations and PS and RS-derived soil information, integrated with quantitative methods to infer spatial patterns of soils across various spatial and temporal scales [*Grunwald*, 2010]. Using a broad range of data sources and methods, DSM aims to provide up-to-date and accurate soil maps to meet the current and future need for soil information. The DSM approach is both data and environmental-centred and so uses the data as a starting point to study the spatial distribution of soils and soil properties. This makes DSM flexible and more suitable in providing soil information for specific applications compared to conventional soil mapping [*Mulder*, 2013].

The basis of DSM is the application of pedometric methods that predict the spatial and temporal distribution of soil types and soil properties. The conceptual framework in which the pedometric methods are applied is the State Factor Equation of soil formation, first introduced by *Jenny* [1941]. This work states that soils can be described by the main environmental soil forming factors, which are: climate, organisms, relief, parent material and time (CLORPT). DSM uses this concept to develop empirical models that relate observations of soil properties with environmental variables describing the main soil forming factors (i.e. CLORPT). Refinements of this modelling framework were made over the years, including the SCORPAN [*McBratney et al.*, 2003] framework, which is spatially explicit, and the STEP-AWBH [*Grunwald*, 2011], which is both spatially and temporally explicit. Typically, the environmental variables are exhaustive, georeferenced data layers, including digitized geological and soil maps, satellite images and derivatives of the latter. There are no prerequisites on the type of model; regression models, regression trees and various other data mining techniques have been proven successful in establishing the statistical relations. Overall, DSM is indeed flexible, quantitative and accurate [*Mulder et al.*, 2011]. Nevertheless, there are some critical points to consider. First, the models are typically not easy to transfer to other regions because the prediction models are based on the feature space of the study area, which may not be applicable in another area. Secondly, compared to conventional soil mapping products, DSM maps are developed for specific purposes rather than for general applications, which reduces its use to a limited public. Finally, DSM is not standardized and the use and interpretation of models by other users requires a clearly written report with supplementary information and instructions [*Mulder*, 2013].

3.1.2 Remote sensing supporting digital soil mapping

Advanced technologies such as remote and proximal sensing offer a wide variety of applications to obtain spatial information on soil forming factors (i.e. CLORPT, SCORPAN model). In this subsection, we highlighted the current RS contribution to obtain information on various CLORPT factors:

Soil properties, like soil mineralogy and soil texture, can be mapped using imaging spectroscopy sensors. While such infrared and visible sensors only measure surface characteristics, radar and gamma radiometry can provide spectral information beyond the vegetative cover and the soil surface. For a detailed overview of remote sensing applications for soil properties see section 3.3.

Characteristic *climate* factors could be represented by air and surface temperature, rainfall and perhaps some measure of potential evapotranspiration. Climate surfaces can be produced from meteorological stations interpolated by Laplacian smoothing splines [*Hutchinson*, 1998a; b] or based on remote sensing data [*Huffman et al.*, 2007; *Mu et al.*, 2011; *Wan*, 2008]. Examples of RS-based climate products, in-situ and model data are *MODIS*, worldclim and *TRMM* products (see Chapter 8).

The main soil forming or altering *organisms* are vegetation or humans, although other organisms can have an appreciable soil-modifying effect locally [*Hole*, 1981]. Estimates of vegetation type, land use and land cover and biomass have all been obtained from visible, infrared and microwave RS and are useful indicators of soil properties and classes [*Chen et al.*, 1999; *Gupta et al.*, 2001]. Examples of data products on land cover and vegetation dynamics are GIMMS, *MODIS* and GlobCover (see Chapter 8).

Topography is mainly derived from DEM's, which are based on Light Detection and Ranging (LiDAR) data, synthetic aperture RADAR (SAR) data and stereo-correlation of optical images. Dependent on the sensor altitude, LiDAR allows for highly accurate and very densely sampling of elevation points which enables the generation of highly resolved digital terrain and surface models [*Brennan and Webster*, 2006; *Hodgson et al.*, 2003]. SAR data are typically processed using interferometric techniques, based on either airborne or spaceborne sensors. Recently, the *ASTER* Global Digital Elevation Map (GDEM), created by stereo-correlation of *ASTER* imagery (30 m), has been made available for free to the public. For Switzerland, the swissALTI^{3D} product is a very precise digital elevation model, which describes the surface of Switzerland without vegetation and surface buildings. It is based on airborne LiDAR measurements and very high-resolution airborne imagery and has an elevation accuracy (ΔZ) of ~1m and a spatial resolution of 2m. Also, the global WorldDEM elevation dataset, with unprecedented resolution (12 m) and ΔZ ~10m, will be available from December 2014. This novel dataset is based on high-precision radar interferometry using the *TerraSAR-X* and *TanDEM-X* satellites. Different primary and secondary attributes can be parameterised from a DEM, such as altitude, slope, aspect, different curvatures, upslope area, compound topographic index, etc. Therefore, DEMs are, arguably, one of the most useful and quantitatively developed factor for predicting soil attributes and soil classes [*McKenzie et al.*, 2000]. See Chapter 8 for further information on data availability.

Parent material information can be obtained from digitized geological maps and geological surveys. Further quantitative information about surface mineralogy and texture can be obtained by imaging spectroscopy, gamma radiometrics as well as geomorphological and weathering models [*Dickson et al.*, 1996]. Additionally, the natural fields of the earth, being gravitational, electrical [*Andriani et al.*, 2001], magnetic [*Galdeano et al.*, 2001] and electromagnetic [*Beard*, 2000], can be used to provide information on the underlying geological structure. Furthermore, regolith maps can be produced from a combination of multi- and hyperspectral and airborne geophysical data. Digitized geological data is available via the OneGeology initiative (see Chapter 8).

3.1.3 Digital soil mapping and geostatistical approaches

As outlined in the previous subsection, DSM may benefit from supplementary RS and PS information. In case of incomplete coverage of the area of interest, exhausted coverage may be obtained by direct interpolation of data gaps, based on RS information as primary data source. This approach is suitable if legacy soil data is scarce or unavailable and exhaustive RS or PS data is available. Alternatively, if legacy soil data are available, soil and terrain attributes, derived from remote sensing or soil proxies, can be used as secondary variables to improve the interpolation of existing soil data [*McBratney et al.*, 2003].

In case remote sensing represents the primary data source, spatial interpolation using geostatistical techniques can be employed to map spatial patterns in areas with sparse soil data. In heterogeneous areas, methods like simple kriging and (generalized) linear models with independent variables, such as slope, curvature, wetness index and soil profile information, have been used to derive soil attribute maps [*Gessler et al.*, 1995; *Moore et al.*, 1993; *Odeh et al.*, 1994; *Philippot et al.*, 2009; *Saby et al.*, 2011]. In complex terrain, however, ordinary kriging is more appropriate, as it adapts to local fluctuations by a restricted neighbourhood search [*Goovaerts*, 1999].

When measurements are sparse or poorly correlated in space, the estimation of the primary attribute is generally improved by accounting for secondary information from other related categorical or continuous attributes such as a DEM, RS data or derived products. PS can be used as a primary data source and RS can be used as one of the secondary data sources to predict soil properties from PS. This way, the large spectral resolution of the PS data can be combined with the spatial coverage of the RS data.

Considering PS, either field or laboratory measurements need to be obtained as primary data source or as a covariable (in co-kriging) for soil spatial prediction on a dense grid. The primary attribute can be predicted with kriging within strata, or some combination of regression analysis and kriging or co-kriging [*Heuvelink and Webster*, 2001; *Knotters et al.*, 1995].

So far, most quantitative relationships have been established between soil attributes and topography derived factors. But there is further evidence of quantitative relationships with the other soil-forming or soil-altering factors, which are generally nonlinear. These factors can be spatially predicted from geographic position using a variety of techniques. The empirical quantitative function linking soil attributes or classes to the CLORPT factors is generally based on various forms of linear models, classification and regression trees, neural networks, fuzzy systems, strengthening models, expert systems, classifications or other methods [*McBratney et al.*, 2003] (Fig. 4).

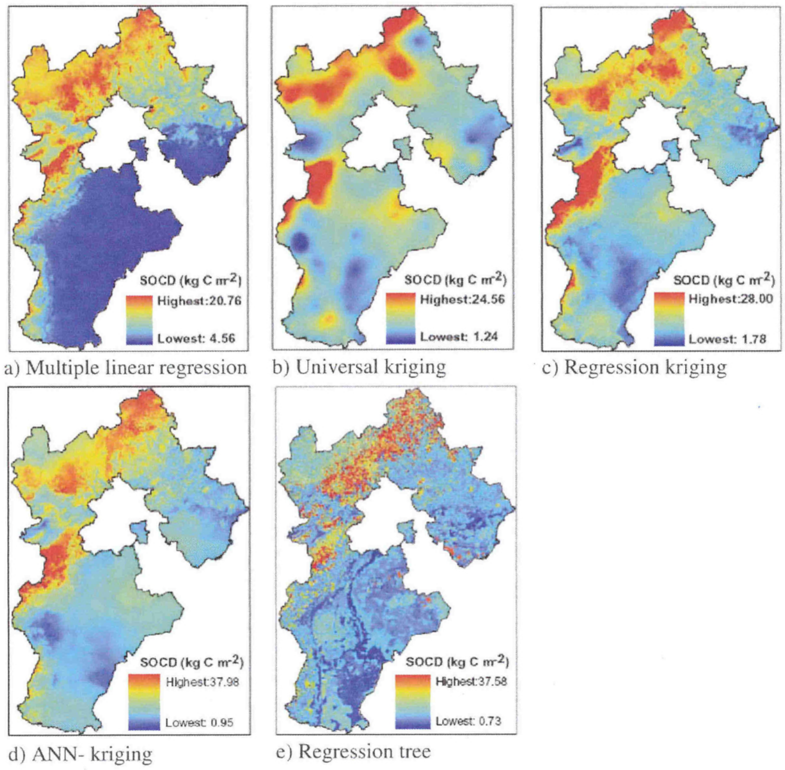

Fig. 4. Spatial distribution maps of soil organic content density (SOCD) based on different spatial predictions for Hebei Province, China. Scale 1:10M [after *Zhao and Shi*, 2010].

3.1.4 Remote Sensing in the context of conventional soil mapping

While DSM studies usually focus on a few key soil properties conventional soil mapping surveys are based on soil taxonomy and soil classification. Thus, the latter provides not only a set of soil properties in top and subsoil, but also taxonomic features such as hydromorphic properties of the soil. Although there is huge potential that RS products support ongoing or planned conventional soil mapping surveys, up to date no soil survey in Switzerland was carried out so far in cooperation with RS expertise. At present the cantonal soil agencies acquire GIS maps from their cantonal GIS centres, but there are hardly any personal resources to process these information for the purpose of soil mapping. The current soil mapping activities at some cantons are mainly performed according the generalized scheme given in Fig. 5. Often soil mapping projects are quite small and the responsible cantonal soil agencies lacking financial support for larger soil mapping surveys. In Switzerland soil information is scarce, for less than one third of the agricultural land (1 Mio hectare) soil information exists as soil maps [*Grob and Keller*, 2011]. Most of these were mapped between the 1970s and 1990s, thus, are sometimes older than four decades. Only a few cantons accomplished so far a 1:5000 soil map. One of the main reasons for this uncomfortable situation is, that the former national soil mapping unit at the Swiss Federal Research Station for Agroecology and Agriculture (FAL) stopped in 1996. Since then the cantons are responsible for soil mapping and are not supported by the federal government concerning reference methods or with new technologies such as remote sensing.

The unfortunate situation induced activities for a national harmonization strategy [*Knecht*, 2004], for digital coding of soil profile information, for converting data coded by earlier data keys and for harmonizing soil maps [*Lüscher*, 2004; *Presler et al.*, 2010]. A major step was the implementation of the web-based Swiss National Soil Information System NABODAT (www.nabodat.ch) in 2011, which now serves as a national, harmonized digital archive for soil information [*Rehbein et al.*, 2011]. At present, eight cantons transferred their soil data to the NABODAT system, while for another 9 cantons the data for transferring their soil data to NABODAT are being processed. As a result, the majority of the soil legacy data generated in soil mapping surveys will be available in the next years in a harmonized manner with the NABODAT soil information system.

These soil legacy data are a valuable information source for new soil mapping activities in Switzerland. Given the performance steps in a conventional soil mapping survey as outlined in Fig. 5, one of the most important step is to acquire and compile all existing environmental information sources and GIS-maps for the SCORPAN factors as mentioned above. For this task the RS products as outlined in the previous chapters provide very valuable information for the pedologist. Bringing together the experience and expert knowledge of the soil scientists with a comprehensive set of thematic maps for the region a first proxy map can be delineated in an effective manner. In addition, the single thematic maps (e.g. geology, terrain attributes, land use, vegetation, and others) might be processed together to provide the soil scientist with a “synthesis” map for those environmental conditions, i.e. the spatial segmentation of soil related environmental covariates. Such a spatial segmentation facilitates to generate the first proxy soil map in conjunction with preliminary soil investigations in the field.

Based on this proxy soil map usually typical representative spatial units are chosen and sites chosen, where soil profiles have to be investigated (so called reference profiles). After that step, the crucial step is to extrapolate the findings for the reference profiles for the whole soil survey area. In this step, in addition to the spatial segmentation any kind of RS product that provides information about the spatial heterogeneity of soil properties is invaluable. Most of the RS products described in chapter 3.3 such as mineralogy, soil texture, soil moisture (in particular in spring time to distinguish the light and heavy textured soils) soil organic carbon, iron and carbonate are very important soil properties helps the soil scientist to perform soil mapping. In conventional soil mapping the soil scientist has usually large experience in field work and delineates the spatial boundaries of the soil map units (i.e. polygons of the final spoil map) with a small soil auger in the field. This information is used then to draw the borders of single soil units on the field map on paper. The field map is often generated on 1:1000 resolution if a target resolution for the final soil map of 1:5000 should be accomplished. However, the accuracy of spatial segmentation of soil map units with such an approach is often discussed and questioned. In fact, large experience is needed by the soil scientist to delineate the spatial boundaries accurately.

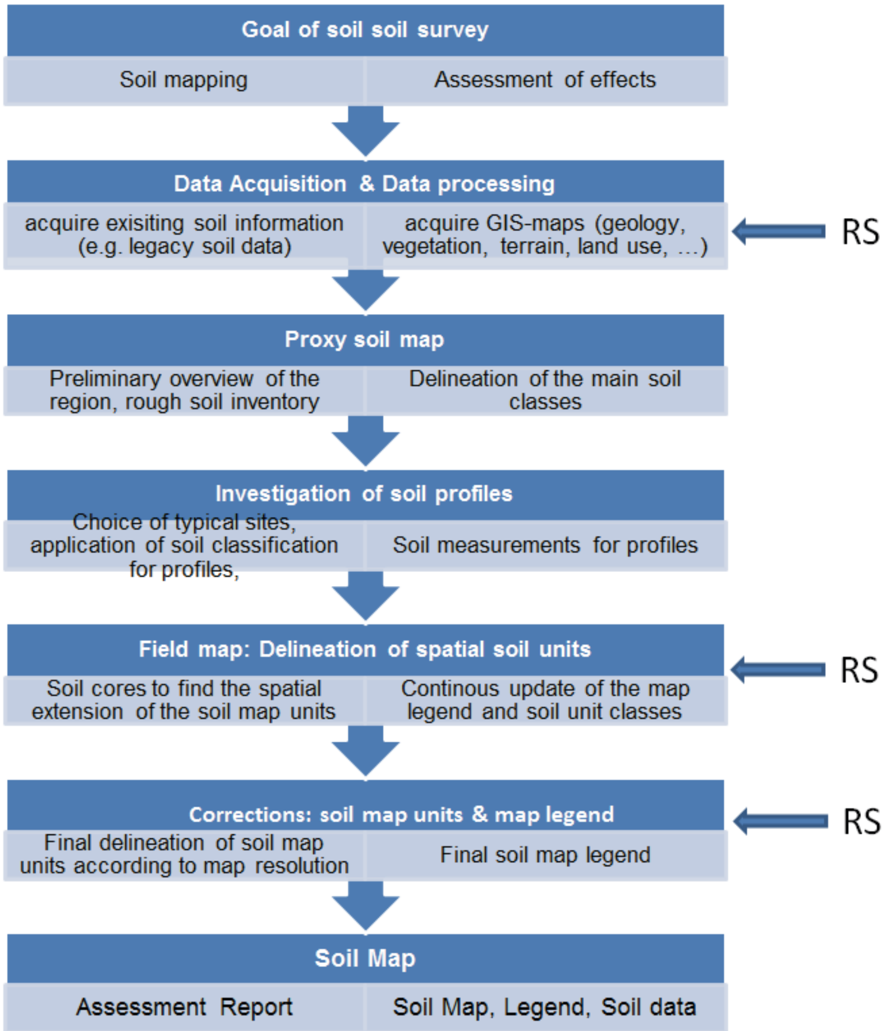

Fig. 5. Generalized performance steps in conventional soil mapping. The arrows indicate for which steps RS products improve soil surveys.

An important issue in classical soil mapping is that single map polygons are delineated if at least one main soil property changes in space in the topsoil or subsoil, e.g. soil texture, soil hydromorphy, organic matter, mineralogy and others. Hence, RS products as proxies for any soil property will improve the spatial segmentation of soil map units. This holds also if RS products would be only available for the top soil. In addition, geostatistical approaches as outlined in chapter 3.1.3 will support this performance step in soil mapping.

In summary, the goals of DSM studies and conventional soil mapping surveys have to be distinguished. DSM studies usually deal with one or a few key soil properties, while conventional soil mapping surveys cope with soil taxonomy and soil classification systems. For both type of approaches RS provides very valuable support, for conventional soil mapping the RS products have to be integrated in various performance steps and into the whole soil mapping procedure. In future, case studies are needed to work out the synergies in detail and to evaluate the benefits of RS for soil mapping surveys in terms of quality of the soil maps, time and costs.

3.2 Remote sensing technologies

Remote sensing of soils covers various spatial, spectral and temporal scales using sensors that utilize different parts of the EM spectrum (Fig. 6). Cutting-edge advances in the quantitative disciplines like RS and PS have laid the foundations for a spatial exploration of soil-system dynamics within a landscape context [*Pennock and Veldkamp*, 2006].

The platform and resolution of RS sensors control the product's accuracy. Compared with ground-based sensors, air or spaceborne sensors have a low signal-to-noise ratio attributed to the larger atmospheric path length, decreased spatial resolution, geometric distortions, and spectral ambiguity caused by recording multiple signals from adjacent features. Furthermore, differences between sensors in available wavelength bands and in the mechanics of imaging influence the accuracy [*Kasischke et al.*, 1997]. In the shorter wavelengths (e.g., the visible part of the electromagnetic spectrum), features can be observed by virtue of reflected solar energy, while in the longer wavelengths (e.g., microwave, thermal EM), sensing of emitted energy predominates.

A number of in-depth reviews have been dedicated to the application of RS to soil mapping and related issues, which demonstrated a significant increase in the efficiency of conventional soil-survey methods when RS data were used [e.g. *Anderson and Croft*, 2009; *Ben-Dor et al.*, 2002; *Dwivedi*, 2001; *Joyce et al.*, 2009; *Kääb*, 2008; *McBratney et al.*, 2003; *Metternicht and Zinck*, 2003; *Metternicht et al.*, 2005; *Metternicht et al.*, 2010; *Mulder et al.*, 2011; *Vrieling et al.*, 2006].

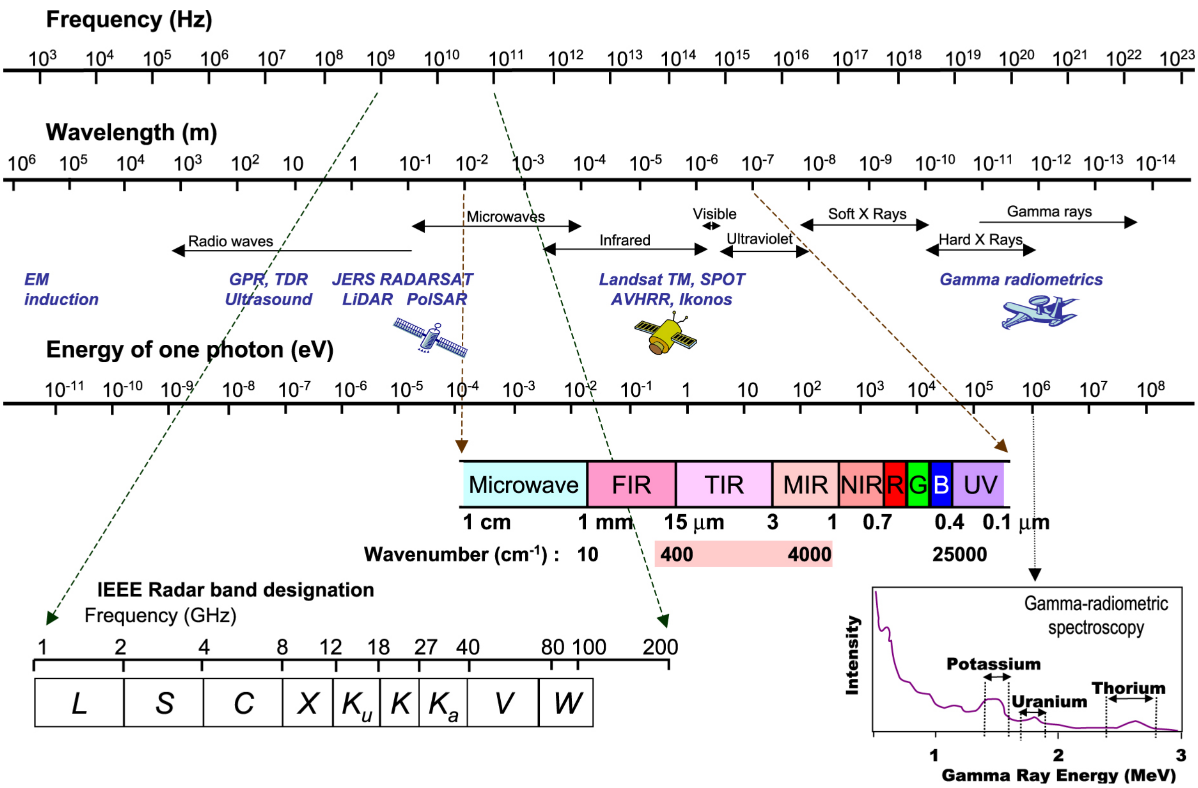

Fig. 6. The EM spectrum, highlighting the useful parts for obtaining information on soil and environmental variables through RS and PS. The boundaries for the visible to infrared spectrum are defines as: VIS: 0.38-0.74; NIR: 0.74-1.4 µm, SWIR: 1.4-3 µm, TIR: 3-15 µm and FIR: 15-1000 µm [after *McBratney et al.*, 2003].

3.2.1 Optical sensors

The spectral reflectance of soil varies depending on the environmental conditions at a specific spatial and temporal scale, but also on land use and management. RS may capture these variations, because it exploits the distinctive nature of energy reflected from materials, from which empirical or analytical models can be constructed. This section provides a summary on the use of optical sensors for soil RS, focusing on imaging spectroscopy and multispectral RS, including thermal RS.

Imaging spectroscopy

Imaging spectroscopy, also known as hyperspectral imaging, is defined as a passive RS technology, acquiring simultaneous images in many spectrally contiguous, registered bands such that for each pixel a reflectance spectrum can be derived [*Goetz et al.*, 1985; *Schaepman et al.*, 2007].

Soils are complex dynamic systems, which are formed and developed as a result of the combined effects of climate, biotic activities, and topography. Soil genesis modifies the chemical, physical, and mineralogical properties of soil surfaces. This process results in distinct spectral absorption features, which can be detected using high-resolution reflectance spectra [*Leone and Sommer*, 2000]. Some of the most significant absorption features occur in the VNIR and SWIR range (0.4 nm to 2.5 µm) (Fig. 7 A,B). These absorption characteristics can vary in their spectral depth, width, and location and therefore serve as diagnostic indicators, which enable us to characterize soil properties. In particular, the amount of organic matter and iron content, particle size distribution, clay mineralogy, water content, soil contamination, CEC and calcium carbonate content, can be determined with imaging spectroscopy [*Ben-Dor et al.*, 2009].

In general, soils have only few recognizable narrow absorption features in the VNIR-SWIR range which become less apparent in the presence of the broad, shallow absorption features, related to iron oxides and organic matter (Fig. 7 A,B). Ferric or ferrous iron causes absorptions in the VNIR spectra, particularly around 860 nm, whereas organic matter results in an overall lowering of the reflectance. In contrast to organic matter and iron oxides, various clay minerals (e.g., montmorillonite, kaolinite, illite, smectite) and carbonates have distinctive narrowband absorption features in the SWIR region between 2000 and 2500 nm. Hence, analysing hyperspectral data is challenging in a variety of ways: (1) the file size of multidimensional imaging spectroscopy data increases linearly with the number of spectral bands. (2) Atmospheric absorption affects particularly hyperspectral data, due to the selective absorption of atmospheric gases and water vapour across the spectral range, which requires sophisticated pre-processing. (3) An overall lower signal-to-noise ratio as compared to multispectral data is another issue related to narrow spectral bandwidths and atmospheric attenuations. (4) A significant band-to-band correlation results in dimensionality issues and consequently reduces the total amount of available bands. (5) Furthermore, imaging spectroscopy data needs to be corrected for BRDF effects, which vary as a function of illumination and viewing geometry and depend on the wavelength as well as structural and optical properties of the surface. Managing these and other challenges convenient and straightforward processing algorithms and methodologies have been developed to analyse imaging spectroscopy data in diverse research disciplines [*Kaufmann et al.*, 2010].

Currently, most imaging spectrometers are airborne sensors (e.g. *AVIRIS*, *HyMAP*, *APEX*, *AISA*, *HySPEX*), in contrast to few spaceborne prototypes (e.g. *Hyperion*, *HICO*).

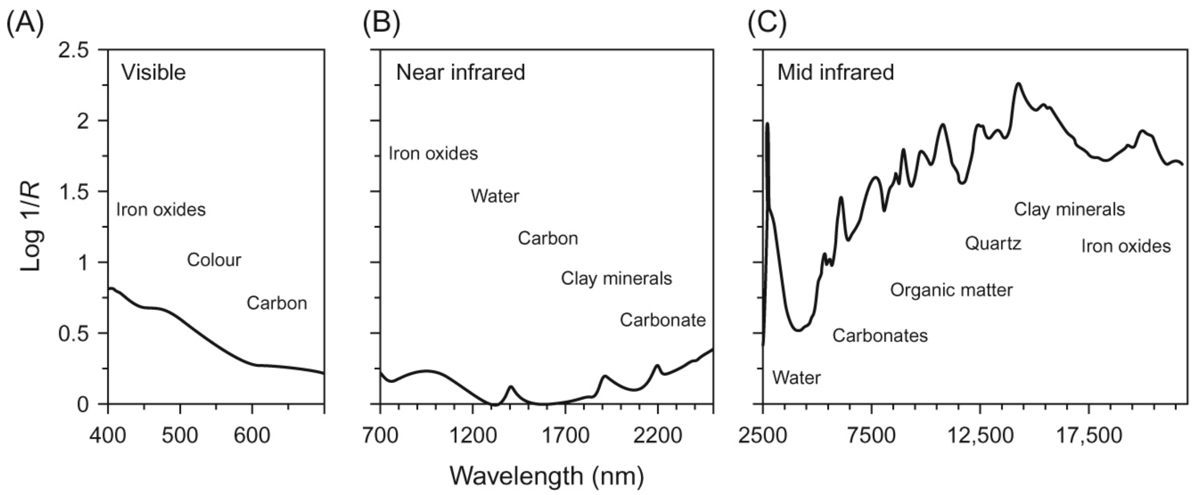

Fig. 7. Typical soil spectrum in the (A) visible (vis), (B) near-infrared (NIR), and (C) mid-infrared (mid-IR) portions of the EM spectrum that indicates spectral ranges of interest, to infer specific soil properties [after *Viscarra Rossel et al.*, 2011].

Multispectral remote sensing

Multispectral sensors record data in fewer bands, resulting in a coarser spectral resolution compared to hyperspectral sensors. Typically, multispectral data has been used to derive information on land cover and land use (Fig. 8), vegetation indices, land degradation and terrain attributes [*Dewitte et al.*, 2012; *Mulder et al.*, 2011]. Over the years, the retrieval of soil attributes with RS has progressed, particularly since the launch of advanced multispectral sensors. Such RS data potentially allow discrimination between crop residues and soil, distinguishing iron oxides, iron hydroxides and iron sulphates, and distinguishing between clay and sulphate mineral species [*Abrams and Hook*, 1995; *Hubbard and Crowley*, 2005; *Hubbard et al.*, 2003]. Examples of advanced spaceborne multispectral sensors with eight or more spectral bands include *ASTER*, *Landsat*, *MERIS*, *MODIS*, and *WorldView2,* among others.

Some multispectral sensors also include spectral bands in the TIR, which measure the thermally emitted radiance from the soil surface. This radiance depends on two factors: (1) the surface temperature, which is an indication of the equilibrium thermodynamic state resulting from the energy balance of the fluxes between the atmosphere, surface and the subsurface soil; and (2) the surface emissivity which is the efficiency of the surface for transmitting the radiant energy generated in the soil into the atmosphere [*Schmugge et al.*, 2002]. The emissivity is conditioned by temperature, the chemical composition, surface roughness, and physical parameters of the surface, e.g. moisture content.

TIR data have been used in combination with other spectral data to discriminate dark clayey soils and bright sandy soils from non-photosynthetic vegetation [*Breunig et al.*, 2008; *Salisbury and D'Aria*, 1992]. Further applications include determining soil salinity and soil moisture as well as establishing soil–vegetation–atmosphere transfer models to estimate root-zone soil moisture.

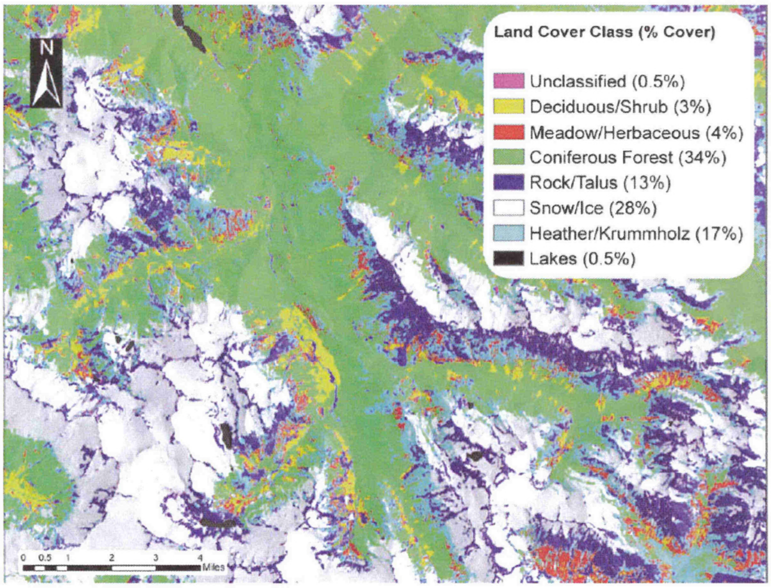

Fig. 8. Land cover map of Thunder Creek, Washington, USA, based on *ASTER* data using the SAM method [after *Meirik et al.*, 2010].

3.2.2 RADAR sensors

Microwave instruments are generally distinguished in active and passive radar sensors, depending on their energy source utilized in the data acquisition (natural vs. emitted microwave radiation). Both systems are highly suitable to quantify soil moisture, whereas active systems are additionally used to derive terrain and soil attributes. The main advantage of radar sensors in comparison to optical and LiDAR sensors is their ability to make ground observations independent of most weather conditions (e.g., clouds, fog). Furthermore, radar sensors can penetrate through soil to a depth that is equal to 10–25% of their wavelength, which equals few millimetres to centimetres depending of the wavelength range [*Lascano et al.*, 1998].

Active microwave systems

Active microwave sensors can achieve high spatial resolutions on a local to regional scale using Synthetic Aperture RADAR (SAR) systems. SAR is the most common imaging active microwave configuration, where microwave pulses are processed together to simulate a very long aperture capable of high spatial resolution. SAR backscatter is directly related to the target dielectric constant [*Moran et al.*, 2000]. The large difference between the dielectric properties of dry soil and moisture enables good calibration of the SAR signal to soil moisture. The active C-band and X-band radars have been used successfully to quantify soil moisture [*Baghdadi et al.*, 2008; *Zribi et al.*, 2011]. Previously SAR sensors were limited by their long revisit time for acquisitions on the same orbital path. For example, *ERS-1* and ASAR were characterized by a repeat cycle of 35 days [*Moran et al.*, 2004]. Nowadays, it possible to map soil moisture with high temporal frequencies (daily to weekly) due to the increasing number of new SAR systems (e.g. *TerraSAR-X*, *Cosmo-SkyMed*, *ASCAT*, *Sentinel-1*) and processing techniques allowing for shorter revisit times. Additionally, the launched

Sentinel-1A and upcoming *Sentinel-1B* satellites of the ESA earth observation program Copernicus will provide complete coverage of Europe, within two to four days. The radiometric, spatial and temporal resolutions of *Sentinel-1* render this mission to a promising platform for operational surface soil moisture retrieval at 1 km over land [*Wagner et al.*, 2012]. Furthermore, retrieval in near real-time using change detection is expected to be technically feasible. In addition to soil moisture, active SAR data are widely used to generate DEMs and other soil attributes, such as soil texture and salinity [*Paulik et al.*, 2014].

Passive microwave systems

Passive microwaves sensors measure the intensity of a soil's microwave emission in a low spatial resolution (~10-50 km) due to the low signal-strength at these wavelengths. With respect to operational spaceborne data, the recent ESA mission *SMOS* operates since November 2009 in the L-band to detect Soil Moisture and Ocean Salinity [*Kerr et al.*, 2010]. This mission delivers soil moisture information at a 50 km spatial resolution within an accuracy of 4%, every three days, and is thus more suitable to detect temporal changes on a regional to global scale. *SMOS* data along with numerical modelling techniques, results in a better estimation of the water content in soil down to a depth of 1-2 m. Estimation of soil moisture in this zone is important for improving hydrological modelling, monitoring photosynthesis and plant growth, and estimating the terrestrial carbon cycle [*Ford et al.*, 2014]. Timely estimates of soil moisture are also important for contributing to the forecasting of hazardous events such as floods, droughts and heat waves.

3.2.3 LiDAR

LiDAR (Light Detection and Ranging) is a widely used data source to generate DEM. Dependent on the sensor flight altitude, LiDAR allows highly accurate and very densely sampled elevation points [*Woolard and Colby*, 2002]. Processing of LiDAR data involves filtering irregularly spaced data points to obtain terrain elevation projected onto a regular grid [*Brennan and Webster*, 2006; *Hodgson et al.*, 2003].

A main limitation for LiDAR based approaches is vegetation cover density. For LiDAR, too small gap fractions in the canopy prevent the laser pulse to reach the ground. Besides several airborne laser scanner systems, spaceborne LiDAR systems (i.e., altimeters and sounding instruments) have atmospheric and cryospheric applications [*Burkert et al.*, 1982; *Spinhirne et al.*, 2005].

3.2.4 Proximal sensors

Mid-infrared Spectroscopy (covering parts of the SWIR and TIR spectrum) contains more information on soil mineral and organic composition than the VNIR, and its multivariate calibrations are generally more robust [*Viscarra Rossel et al.*, 2006b]. The main reason is that defined molecular vibrations of soil components occur in the mid-IR, while only their overlapping combination and overtone peaks can be detected in the NIR [*Stenberg et al.*, 2010]. This combined signal results in a multitude of bands for even simple compounds. One caveat on the use of mid-IR spectroscopy is the presence of distortions due to specular reflection [*Reeves et al.*, 2005]. Specular reflection causes spectral distortions depending on the concentration of the material and the particular band (frequency) in question [*Reeves*, 2010].

Electromagnetic induction is a highly adaptable non-invasive technique that measures the apparent bulk electrical conductivity (EC_a) of the soil [*de Jong et al.*, 1979]. Electromagnetic induction is particularly useful for mapping saline soils and for precision agriculture (Fig. 9). Furthermore, the instruments can be placed in airborne platforms for data collection at the catchment and regional scale.

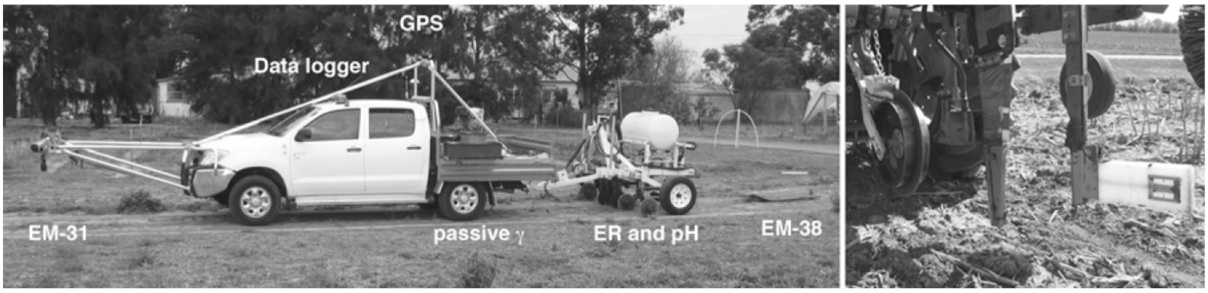

Fig. 9. Multisensor platforms. (left) A multisensor platform with electromagnetic induction, passive gamma-ray spectrometry, electrical resistivity, and pH sensors and (right) one with mechanical, electrical, and optical sensors [after *Viscarra Rossel et al.*, 2011].

Soil electrical conductivity (or its reciprocal soil electric resistivity) reflects a combination of soil mineralogy, salts, moisture and texture, hence, it is a good compound measure of soil (Fig. 10). Measurements of resistivity usually require four electrodes; two electrodes are used to apply the current (current electrodes) and two are used to measure the resulting potential difference (potential electrodes). Such proximal sensing offers the possibility of producing high-resolution maps of the soil electrical conductivity. Furthermore, regression equations have been developed to predict and map moisture content, topsoil thickness, and clay content [*Samouelian et al.*, 2005].

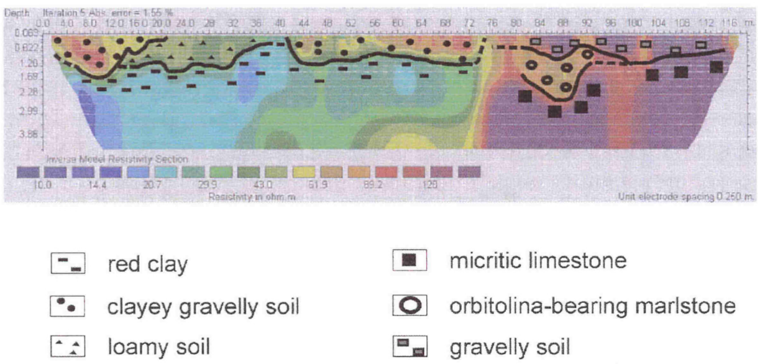

Fig. 10. Soil transect based on electric resistivity tomography and soil cores to create a 2D soil texture/mineralogy map [after *Coulouma et al.*, 2010].

Induced polarisation measurements are essentially an extension of the four-electrode resistivity technique described above. Induced polarisation operates by first applying an electric current between a current electrode pair and the resulting voltage induced in the soil is measured between a potential electrode pair. However, induced polarisation captures both the charge loss (conduction) and the charge storage (capacitance) characteristics of the soil. Induced polarisation instruments have been used in hydrogeophysical applications, e.g. to infer soil hydraulic properties in the vadose zone [*Börner et al.*, 1996].

Magnetic sensors, or, magnetometers, measure variations in the strength of the earth's magnetic field and the data reflect the spatial distribution of magnetization throughout the ground. Magnetisation of naturally occurring materials and rocks is determined by the quantity of magnetic minerals and by the strength and direction of the permanent magnetisation carried by those minerals [*Hansen et al.*, 2005]. Typically, magnetics has been used for the detection of geological bodies. However, there is increasing use of the technique for near-surface applications for example; to better understand soil genesis and formation [*Mathé and Lévêque*, 2003]; to detect anthropogenic pollution on top soils through their associations with Fe-oxides; and for rapid identification and mapping of soil heavy metal contamination [*Jordanova et al.*, 2008].

Seismic reflection methods are sensitive to the speed of propagation of various kinds of elastic waves. The elastic properties and mass density of the medium in which the waves travel control the velocity of the waves and can be used to infer properties of the earth's subsurface. Reflection seismology is frequently used in exploration for hydrocarbons, coal, ores, minerals, and geothermal energy. It is also used for basic research into the nature and origin of rocks that make up the Earth's crust. Furthermore, it can be used in near-surface application for engineering, groundwater and environmental surveying [*Viscarra Rossel et al.*, 2011].

Ground Penetrating Radar (GPR) is similar to reflection seismology, as it uses the transmission and reflection of high frequency (1 MHz to 1 GHz) EM waves in the soil (Daniels et al. 1988). The resolution of GPR images can be varied through the use of different antennae frequencies. Typically, higher frequencies increase the resolution at the expense of penetration depth. GPR has been extensively used for various environmental applications [*Knight*, 2001], including the determination of soil water content [*Huisman et al.*, 2003] (Fig. 11).

Fig. 11. A ground-penetrating radar (GPR) system [after *Viscarra Rossel et al.*, 2011].

Magnetic resonance sounding uses a nuclear magnetic resonance principle that is used in medical brain scanning (i.e. magnetic resonance imaging (MRI)) to measure subsurface free water and hydraulic properties [*Lubczynski and Roy*, 2004]. It is also known as surface nuclear magnetic resonance and can be used to measure water content and porosity to depths up to 1500 m. *Paetzold et al.* [1985] used the technique to measure soil water content and concluded that the nuclear magnetic resonance signal is a linear function of volumetric water content and is not affected by clay mineralogy, soil organic matter, or texture. They concluded that the nuclear magnetic resonance signal is uniquely related to liquid water in soils and rocks.

Gamma-Ray Spectrometry, also known as γ-radiometrics, provides a direct measurement of natural gamma radiation from the top 30 to 45 cm of the soil [*Bierwith*, 1996]. A gamma-ray spectrometer is designed to detect the gamma rays naturally emitted from the earth surface [*Grasty et al.*, 1991] (Fig. 12). Airborne radiometrics surveys measure the radiation of gamma-emitters, like ^{40}K and daughter radionuclides of ^{238}U and ^{232}Th. As the concentration of these radioelements varies between different rock types, we can use the information to map spatial variation of parent material (soil-forming rocks). Interpreting the surface geology requires an understanding of the nature of the surficial materials and their relationship to bedrock geology. It can also be considered as a direct, albeit compound, a measure of the mineralogical and textural composition of the soil itself and it has also been applied to estimate variation in surface soil moisture content [*Carroll*, 1981] and regolith characterization [*Martelet et al.*, 2013].

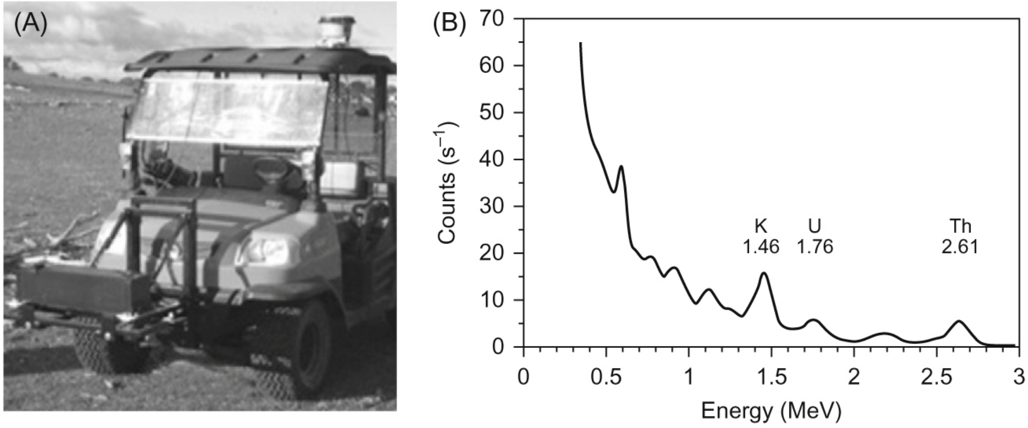

Fig. 12. (A) A proximal passive γ radiometric sensor mounted on a multisensory platform and (B) a gamma-ray spectrum showing the energies of the potassium (K), uranium (U), and thorium (Th) bands [after *Viscarra Rossel et al.*, 2011].

Table 1. Suitable proximal soil sensors, other than VNIR-TIR, for acquiring soil information [after *Viscarra Rossel et al.*, 2011].

Sensing technology	Depth (m)	Dependent property	Inferred properties	Technological development	Methodological development	Approximate cost $US
Electromagnetic induction (EMI)	<1–6 m	Resistivity, magnetic, permeability, permittivity	Conductivity, soil water and solutes, texture, temperature, salinity	Mature	Mature	>20 k
Electrical resistivity	<1–<30 m	Resistivity	Conductivity, soil water and solutes, texture, temperature, salinity	Mature	Mature	>20 k
Induced polarization	<1–<50 m	Resistivity, capacitance	Conductivity and polarization, soil water, hydraulic properties, lithology	Mature	Developmental	>50 k
Magnetics	<1 m to <10 km	Magnetization	Magnetic minerals Fe-oxides, structure, lithology	Mature	Mature/researchable	>40 k
Gravity	>1 m to <100 km	Density	Lithology, hydraulic properties	Mature	Researchable	>60 k
Seismic	<1 m to <500 km	Elastic moduli, acoustic impedance, density	Soil layering, soil structure, soil depth, soil density, lithology	Mature	Researchable	>50 k
Ground penetrating radar (GPR)	<1 m to <10 m	Resistivity, magnetic permeability, permittivity	Soil water, texture, soil depth	Mature	Researchable	>40 k
Magnetic resonance sounding	<1 m to <1.5 km	Proton density	Soil water, porosity, hydraulic properties	Emerging	Developmental	
γ-radiometrics	<1 m	Radioisotopes of Cs, K, U, Th	Total K, mineralogy, clay content, soil type	Mature	Researchable	>30 k

3.3 Remote sensing products

In the following subsections we review the different soil attributes that can be determined by PS and RS for bare or sparsely vegetated soil. These soil attributes encompass globally important soil properties such as texture, organic matter, moisture and mineralogy as well as soil properties of local to regional relevance such as iron content, soil salinity and carbonates [*Arrouays et al.*, 2014].

3.3.1 Mineralogy

Surface mineral composition can be determined from the RS spectral signature of rock outcrops and bare in-situ soils. In order to discriminate between different minerals, subtle differences in the spectral signature throughout the VNIR to TIR may be used. For this, airborne or spaceborne data having fine spectral resolution are needed, which allow to detect subtle differences in the spectral fingerprint of the mineralogical composition. Furthermore, a high spatial resolution is beneficial to reduce spectral mixing effects from different land cover types. Airborne imaging spectroscopy data are highly suitable for this task (e.g. *AVIRIS*, *HyMAP*), given its high spatial and spectral resolution [*Green et al.*, 1998]. For example, *AVIRIS* data has been used to analyse the variation in type and their mineralogical and chemical compositions, by mapping SiO_2 and Al2O$_3$ in order to estimate the degree of soil weathering [*Bedini et al.*, 2009; *Galvão*, 2008; *Green et al.*, 2003; *Kruse et al.*, 2003; *Launeau et al.*, 2004; *Martini et al.*, 2004]. But also synergies of multispectral satellite data have been used to determine mineral compositions. For example, the combination of *Landsat TM* data and *ASTER* data revealed promising results to differentiate the general lithological variability based on *Landsat TM* and to distinguish different mineral groups based on *ASTER*. Similar results can be obtained with the *ASTER* Geoscience Products [*Cudahy*, 2012]. The spectral features of typical rocks on Earth are mostly found in the TIR region, where quartzite, carbonate, silicate and mafic minerals can be discerned. In local studies, advanced methods for deriving minerals from *ASTER* data have resulted, in classification accuracies up to 86%. However, the spatial and spectral resolutions of other multispectral satellites, such as *Landsat TM* or *MODIS*, have been found to be too coarse for determining mineral composition [*Dobos et al.*, 2000; *Kettles et al.*, 2000; *Teruiya et al.*, 2008].

The analysis of mineralogy with spectral PS has made great progress over the last years. Nowadays, several institutes provide spectral libraries with comprehensive collections of a wide variety of materials. For example, the *ASTER* spectral library version 2.0, which is a collection of contributions from the Jet Propulsion Laboratory, Johns Hopkins University and the United States Geological Survey, is a widely used spectral library containing over 2400 spectra of a wide variety of minerals, rocks, vegetation and manmade materials, covering the wavelength range 0.4–15.4 µm [*Baldridge et al.*, 2008]. Similarly, the USGS Spectral Library offers a wide range of mineral spectra [*Clark et al.*, 2007].

The PRISM and Tetracorder tool, on the other hand, consist of a set of algorithms within an expert system decision-making framework for soil and terrain mapping. The expert systems can compare the spectra of materials of unknown composition with reference spectra of known materials. For example, the USGS spectral library contains soil mineral properties and land cover types from all over the world. This spectroscopic analysis allows the composition of the material to be identified and characterized [*Kokaly*, 2011]. The results obtained with the Tetracorder show that many different minerals can be identified as has been shown in Fig. 13 [*Clark et al.*, 2003].

Examples of powerful subpixel unmixing analysis tools are the Successive Projection Algorithm (SPA) [*J Zhang et al.*, 2008], Spectral Angle Mapper (SAM), Constrained Energy Minimization (CEM) and spatial–spectral endmember extraction (SSEE) tool [*García-Haro et al.*, 2005; *Kruse et al.*, 1993; *Rogge et al.*, 2007; *Rowan and Mars*, 2003; *X Zhang et al.*, 2007].

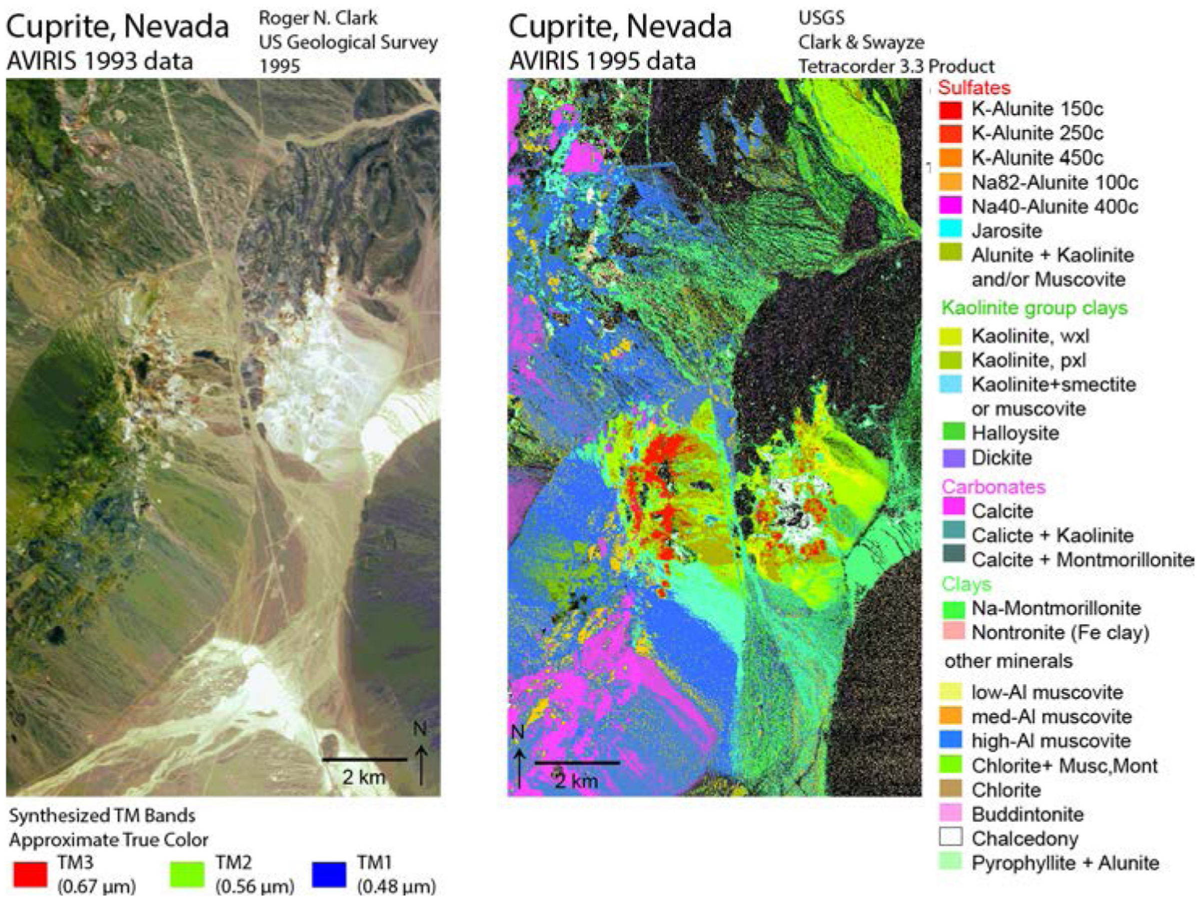

Fig. 13. (Left) True colour composite of Cuprite, Nevada and (right) the corresponding mineral map derived from AVIRIS data [Reprinted after *Clark et al.*, 2003].

3.3.2 Soil texture

In standard soil analysis, soil texture classes, such as silt, sand or clay are determined by their particle size distribution or physical texture. In RS, soil texture is typically determined using specific absorption features to differentiate between clay-rich and quartz-rich soils (Fig. 14). Clay minerals have typical hydroxyl absorption at 2200 nm; this feature can be captured with bands 5 and 6 of *ASTER*, referred to as the SWIR Clay Index [*Chabrillat*, 2002]. The presence of quartz can be detected using thermal bands between 8000 nm and 9500 nm in which the restrahlen feature (reflectance peak of silica) occurs, which correspond with bands 10 to 14 of *ASTER*. The combination of *ASTER* SWIR bands 5 and 6 and TIR bands 10 and 14 can then be used to discriminate both dark clayey soils and bright sandy soils from non-photosynthetic vegetation on a local scale, but organic matter influences the results [*Breunig et al.*, 2008; *Salisbury and D'Aria*, 1992]. Principal component analysis of multispectral

ASTER imagery has also been used to determine broad texture classes [*Apan et al.*, 2002]. In contrast, most other multispectral sensors are not designed to capture the necessary spectral information related to soil texture.

In PS, soil texture is typically determined by multiple linear regression (MLR) or partial least-square regression (PLSR). Results show that these methods are useful tools for predicting soil texture, but calibration of the models is based on local conditions and therefore these models will typically have a reduced accuracy outside the studied areas [*Demattê et al.*, 2007; *Minasny et al.*, 2008; *Mulder et al.*, 2011; *Thomasson et al.*, 2001; *Viscarra Rossel et al.*, 2006a].

In contrast to the use of optical imagery, there is little experience in using radar for soil texture retrieval. *Singh and Kathpalia* [2007] developed a modelling approach based on a Genetic Algorithm, which included empirical modelling to simultaneously retrieve soil moisture, roughness and texture from the dielectric constant derived from ERS-2 SAR backscatter data. Although the results were in agreement with field observations, they concluded that there were problems with the retrieval of input variables of the model.

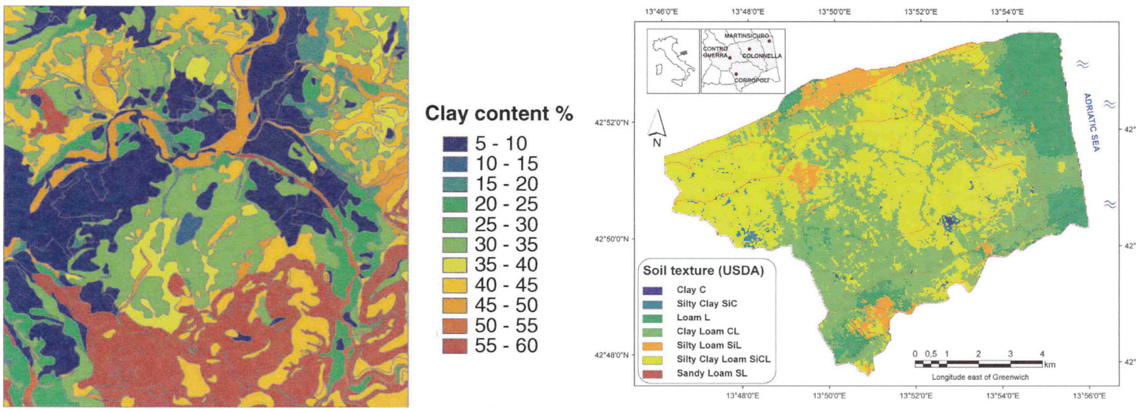

Fig. 14. (Left) Nominal clay content (%) for distinct soil units based on predictions using Bayesian belief networks [after *Mayr and Palmer*, 2006]. (Right) Soil texture based on regression kriging [after *Marchetti et al.*, 2010].

3.3.3 Soil moisture

Microwave RS of soil moisture content is based on the contrast in dielectric properties between dry soil and water derived from the backscatter data. The boundaries of the backscatter data are set on the basis of a long-term change detection approach. An advanced index on soil moisture is the Soil Water Index (SWI) [*Wagner et al.*, 2007], which combines ERS/ASAR and METOP data to achieve a spatial resolution of 1 km on a daily basis (Fig. 15). The index is particularly useful for monitoring changes in soil water content over time, but is unsuitable to quantify the soil water content [*Wagner and Scipal*, 2000; *Wagner et al.*, 2007]. The overall quality of the SWI data, compared to in situ soil moisture data from 664 stations, averages a Pearson correlation coefficient of 0.54 [*Paulik et al.*, 2014]. The recently launched passive microwave *SMOS* (Soil Moisture and Ocean Salinity) and future satellite *SMAP* (Soil Moisture Active Passive) will have a global coverage with 1 km resolution and a temporal resolution up to approximately 3 to 5 days. The modelled surface soil moisture (0–3 cm) is expected to be accurate to within 4.0% volumetric water content [*Panciera et al.*, 2009; *Wigneron et al.*, 2007]. The successfully launched *Sentinel-1A* and upcoming *1B* satellites (expected launch in in 2016) are characterized by improved spatial, temporal and radiometric resolutions. The retrieval of soil moisture will further benefit from the cross-polarization ability to correct for seasonal vegetation effects in the co-polarized backscatter measurements. Assuming the successful operation of both *Sentinel-1* satellites, the specifications of a potential surface soil moisture product will comprise a spatial resolution of 0.5-1 km and a temporal resolution 3-6 days in Europe with a high accuracy of 0.04 to 0.08 m^3 / m^{-3} over grassland and agricultural areas, excluding forests and steep terrain [*Gruber et al.*, 2013].

Imaging spectroscopy indices for estimating surface soil moisture content have been established using the reflectance in the SWIR region [*Haubrock et al.*, 2005; *Haubrock et al.*, 2008; *Lobell and Asner*, 2002]. However, most retrieval algorithms were limited in their accuracy due the presence of vegetation. A recent study improved this drawback by accounting for a vegetation-cover influence of up to 75% [*Spengler et al.*, 2013].

A different approach to estimate soil moisture is using surface energy balance models. These studies are typically done on the plot to local scale and produce spatio-temporal predictions of actual evapotranspiration, which can be linked with soil water. There are several models available; the most widely used are (1) the Soil Energy BALance (SEBAL), in which soil and vegetation contributions to ET are aggregated [*Bastiaanssen et al.*, 2005]; (2), the Two-Source Energy Balance (TSEB) modelling approach, which discriminates between soil and vegetation [*Aly et al.*, 2007]; and (3), the Surface Energy Balance System (SEBS) (Su, 2002) which uses both the optical and thermal parts of the electromagnetic spectrum to estimate turbulent atmospheric fluxes and surface evaporation [*Van Der Kwast*, 2009]. *ASTER* and *MODIS* images have been used for retrieving the surface variables required as inputs for energy balance modelling [*French et al.*, 2005; *Su et al.*, 2005]. The main difficulties using surface energy balance models are obtaining all the necessary data at the proper spatial resolution and the calibration of the model.

Currently, the most advanced approaches used for estimating root zone soil moisture are based on assimilation of remote sensing observations into soil–vegetation–atmosphere transfer (SVAT) model. These models can be divided into thermal RS and water and energy balance (WEB) approaches. The WEB-SVAT (Water and Energy Balance - Soil Vegetation Atmosphere Transfer Modeling) model uses measured precipitation and predicted evapotranspiration. The model is based on forcing a prognostic root-zone water balance model with observed rainfall and predicted evapotranspiration. In RS SVAT approaches, the radiometric temperature is derived from thermal RS and combined with vegetation information obtained at the VNIR wavelengths in order to solve the surface energy balance; this method does not explicitly quantify soil moisture but uses a thermal-based proxy for the availability of soil water in the root zone and the onset of vegetation water stress [*Crow et al.*, 2008].

Under laboratory conditions, spectral PS with statistical methods has been used for quantifying soil water content. Examples of such methods are (1) the soil line, which plots the red-band as a function of the NIR-band [*Baret et al.*, 1993; *Demattê et al.*, 2006] and (2) MLR with the water absorption features, centred at 1400, 1900 and 2200 nm, as the independent variables and measured soil moisture as the dependent variable. However, the latter method will most likely not work under field conditions, owing to the strong absorption of radiance by water vapour in the atmosphere.

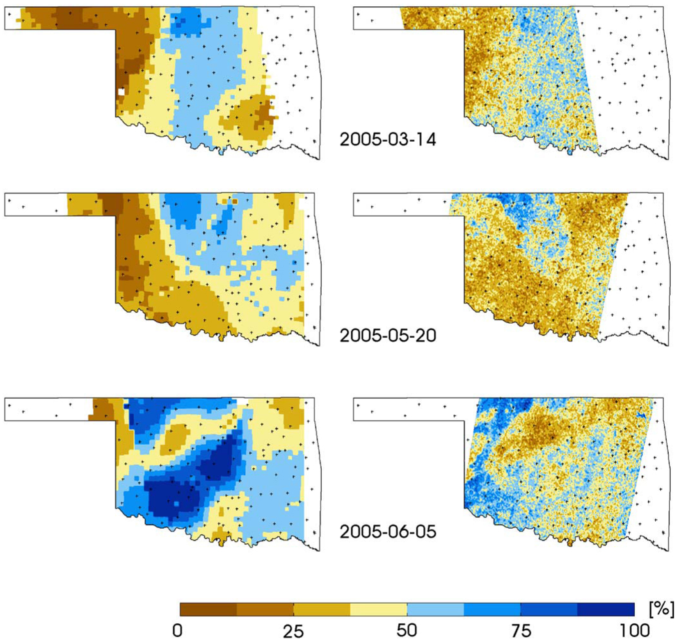

Fig. 15. (Left) Surface soil moisture maps of Oklahoma retrieved from ERS scatterometer in a 50 km spatial resolution and (right) ASAR GM measurements in 1 km spatial resolution for three different dates in spring 2005 [after *Pathe et al.*, 2009].

3.3.4 Soil organic carbon

Soil colour is a first order indicator to estimate soil organic carbon (SOC); typically, dark soils contain more soil organic matter than pale soils. This darkening of soil with higher SOC content is caused by saturated organic matter and to variation in the composition and quantity of black humic acid and soil moisture [*Viscarra Rossel et al.*, 2006a]. However, some soil colour systems (e.g. Munsell HVC [*Munsell*, 1912]) are based on subjective perception and comparison, which results in a non-uniform system not suitable for quantification of SOC [*Viscarra Rossel et al.*, 2006a].

Using imaging spectroscopy for mapping SOC enables robust analysis of reflectance patterns beyond the visible spectrum (Fig. 6, 16). Used techniques employed the shape of the reflectance spectrum, absorption features analysis and principal component analysis [*Palacios-Orueta and Ustin*, 1998; *Palacios-Orueta et al.*, 1999]. Alternatively, regression modelling can be used [*Ben-Dor et al.*, 2002]. Previously, such methodologies have been employed successfully on spaceborne and airborne imaging spectroscopy data [*Gomez et al.*, 2008; *Selige et al.*, 2006; *Stevens et al.*, 2010].

However, most research determining SOC using spectral information has been performed at the plot scale (<1 km^2). Here, spectral data is usually obtained from PS thereby reducing the effect of vegetation on the spectral response. Correlation coefficients in the range of $0.87<R^2<0.98$, between spectrally measured and chemically analysed samples, have been obtained using mid-infrared and combined diffuse reflectance spectroscopy [*Barnes et al.*, 2003; *Chang*, 2002; *McCarty et al.*, 2002; *Viscarra Rossel et al.*, 2006a].

Mapping SOC over vast areas, without extensive calibration by soil samples, can be achieved using spectrally-based indices. The SOC content is then determined based on the constituents of SOC: cellulose, starch and lignin; good relations have been found for indices based on the visible part of the spectrum (R^2=0.80) and for the absorption features related to cellulose (around 2100 nm) (R^2=0.81). The best index-based relations compared to results for PLSR (R^2=0.87). PLSR proved to be much less sensitive towards extrapolation of the model beyond SOC levels used during the calibration. Although the indices seem promising, they must still be tested on spaceborne sensors, which currently have lower signal-to-noise ratio. Application in areas having substantial vegetation cover will be a challenge as well [*Bartholomeus et al.*, 2008].

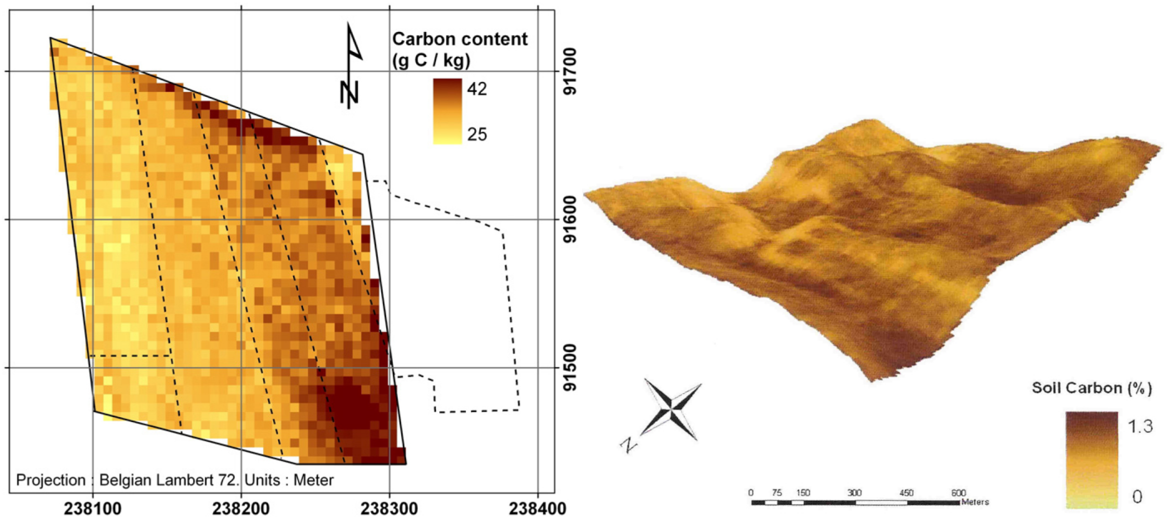

Fig. 16. (Left) Map of SOC content in a freshly ploughed field after land consolidation based on combined *CASI–SASI* imaging spectroscopy data. Dashed lines denote boarders of the original, separated fields [after *Stevens et al.*, 2006]. (Right) Soil carbon map derived from imaging spectroscopy data of the bare soil of an agricultural field, draped on a LiDAR derived DEM (15x exaggerated) [after *McCarty et al.*, 2010].

3.3.5 Iron content

Soil iron can be seen as an indicator of soil fertility and the age of the sediments [*Bartholomeus et al.*, 2007]. Over the years, PS has proven to be useful for determining soil iron content in soil samples and at the plot scale [*Demattê*, 2002; *Nanni and Demattê*, 2006]. But also, RS imagery has been successfully used for determining the presence of iron over areas up to 500 km^2. Both soil colour [*Escadafal*, 1993] and absorption features have been used to derive iron content [*Farrand and Harsanyi*, 1997; *Palacios-Orueta and Ustin*, 1998;

Warell, 2003]. Iron oxide and iron hydroxides have specific absorption features that are located in the VNIR and can be measured from multispectral or imaging spectrometer images [*Abrams and Hook*, 1995]. However, these absorption features are less distinct in the presence of vegetation, which hampers retrieving of soil iron [*Xu et al.*, 2004].

Only few methods have been developed to quantify soil iron content (Fig. 17). Though *Landsat TM* has been used for this purpose, owing to the low spectral resolution the absorption features were not unequivocally discernable and therefore the results were considered inaccurate [*Deller*, 2006]. *Bartholomeus et al.* [2007] were among the first quantifying soil iron content on the basis of airborne optical data. They determined the iron content in Mediterranean soils in partly vegetated areas, using ground-based spectral reflectance and airborne imaging spectroscopy. The use of two iron-related absorption features as well as a ratio-based Redness Index, resulted in moderately good correlations (R^2=0.67 and R^2=0.51, respectively) on samples measured under laboratory conditions. Unfortunately, the relations were comparably weak (R^2=0.26) when applied to airborne *ROSIS* (Reflective Optics System Imaging Spectrometer) data. The relations appeared to be sensitive to vegetation cover, but a combination of the Redness Index plus relations based on the absorption feature, made the model more robust against the influence of vegetation cover [*Bartholomeus et al.*, 2007].

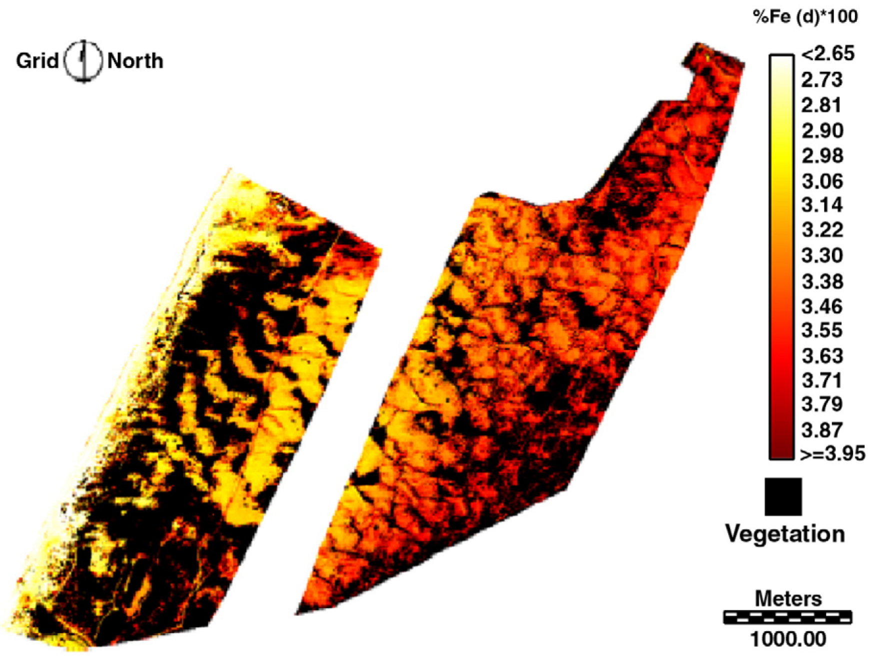

Fig. 17. Map of free iron oxides at the Ashdod sand dunes, Israel [after *Ben-Dor et al.*, 2008].

3.3.6 Soil salinity

In arid and semi-arid climates, precipitation is insufficient to maintain a regular percolation of rainwater through the soil, so soluble salts accumulate, with consequences for soil properties, such as structure, and land suitability.

Both radar and optical RS data have been used for mapping soil salinity. Microwave remote sensing of salinity is based on the dielectric properties of the soil, since salinity is a key element of the electric conductivity [*Aly et al.*, 2007]. The dielectric constant is a complex number consisting of a real part, which is related to soil moisture, and an imaginary part, which is related to salinity. Using inverse modelling, the imaginary part can be calculated and calibrated with soil salinity [*Bell et al.*, 2001; *Taylor et al.*, 1996; *Yun et al.*, 2003]. Soil salinity classes have been successfully derived on a local scale (<500 km^2) with the C-, P-, and L-bands of airborne and spaceborne radar systems; best results are obtained using L-band data because long wavelengths penetrate soil and vegetation to a greater extent than higher frequencies [*Bell et al.*, 2001; *Lasne et al.*, 2008; *Taylor et al.*, 1996].

The spectral response patterns of saline soils are a function of the quantity and mineralogy of the salts they contain [*Mougenot et al.*, 1993]. Using spectral absorption features, spectral PS can be used to provide information on the presence of salt minerals and it enables salt-affected soils to be quantified [*Weng et al.*, 2008]. Salinized soils have distinctive spectral features in the VNIR parts of the spectrum, related to water in hydrated evaporite minerals. They show absorption features at 505 nm, 920 nm, 1415 nm, 1915 nm and 2205 nm. However, laboratory spectral analyses revealed that salt affected soil samples did not exhibit all of the diagnostic absorption features that were found in the spectra of the pure salt minerals. Yet, the regression models had accuracies up to R^2=0.8 [*Farifteh et al.*, 2008].

Salt scalds and highly salinized soil show additional absorption features at 680, 1180 and 1780 nm. These features enable the recognition of minerals, such as gypsum, bassanite, and polyhalite, which can be used as salinity indicators. Another informative property is that, at approximately 2200 nm, hydroxyl features become less pronounced when samples are more saline. The reduction of the 2200 nm absorption intensity may be a result of a loss of crystallinity in clay minerals. Yet another potentially usable characteristic, is the overall decrease in slope of the reflection curve between 800 and 1300 nm as samples become more saline [*Taylor and Dehaan*, 2000]. Using RS on a local scale (<10^4 km), broad salinity classes can be mapped with *ASTER* [*Melendez-Pastor et al.*, 2010], *HyMAP* [*Dehaan and Taylor*, 2003], *Landsat TM* and *ALI* imagery - the latter two using the Salinity Index and the Normalized Salinity Index (NSI) [*Bannari et al.*, 2008; *Jabbar and Chen*, 2008; *Odeh and Onus*, 2008]. *Weng et al.* [2008] were able to discriminate five classes of saline soils with Hyperion data for an area of about 1200 km^2. Alternative methods for mapping saline areas are based on detecting the presence of salt scalds and halophytic vegetation. However, the spectral resolution must be high in order to detect the different vegetation types [*Dehaan and Taylor*, 2001].

A major constraint to using PS and RS for mapping salinity is related to the fact that there is a strong vertical, spatial and temporal variability of salinity in the soil profile. Spectral data acquisition does not allow information to be extracted from the entire soil profile, since only the Earth surface is observed. This can be overcome by integrating RS data with simulation models and geophysical surveys [*Farifteh et al.*, 2006; *Metternicht and Zinck*, 2003; *Mougenot et al.*, 1993]. Direct and precise estimation of salt quantities is difficult using satellite data with a low spectral resolution because these fail to detect specific absorption bands of some salt types and the spectra interfere with other soil attributes [*Mougenot et al.*, 1993].

3.3.7 Carbonates

Optical RS allows distinction between common carbonate minerals on the basis of unique spectral features found in the SWIR, and especially in the TIR region. Here, the minerals have a low emissivity from 1095 up to 1165 nm and high emissivity from 8125 to 10950 nm. The Calcite Index, for example, is based on this difference in emissivity and has been successfully used on single *ASTER* images of 60*60 km [*Yoshiki et al.*, 2002; *Yoshiki et al.*, 2004]. Alternatively, the specific absorption features of carbonate have been analysed with derivative analysis on PS data. Derivatives of second order or higher should be relatively insensitive to variations in illumination intensity, whether caused by changes in sun angle, cloud cover, or topography [*Hu*, 2007; *Plaza et al.*, 2008]. Under laboratory conditions this method worked well (R^2=0.64), but when applied to airborne data with a pixel size of 25 m^2, the performance decreased (R^2=0.46). This was attributed to radiometric and wavelength calibration uncertainties as well as possible residual atmospheric effects [*Lagacherie et al.*, 2008].

3.3.8 Soil degradation and contamination

Imaging spectroscopy enables the assessment of important soil erosion variables, such as water content and surface roughness [*Haubrock et al.*, 2005; *Haubrock et al.*, 2008]. Furthermore, spectroscopic data can be used to map post-fire soils and pin point water-repellent soil areas that tend to be potentially highly erodible [*Lewis et al.*, 2004].

The spectral difference between severely eroded soils and intact topsoil has previously been used to map surface erosion processes [*Demattê and Garcia*, 1999]. In a study area in southern France, various soil erosion states have been identified based on the ratio between developed substrates and components of the parent material [*J Hill et al.*, 1994]. Their corresponding end-member spectra were subsequently used to parameterize a spectral mixture model to map the spatial extent of soil erosion [*J Hill et al.*, 1995]. The results highlighted that different erosion levels could be mapped with an accuracy of about 80%, which proved superior to applying the approach of *Landsat-TM* imagery [*J Hill et al.*, 1995].

Another approach to assess soil erosion and soil degradation status is based on quantitative estimates of specific soil chemical properties. In a study area in south-eastern Spain imaging spectroscopy data have been used to identify SOC concentrations indicating soil deposition and erosion states; high SOC concentrations in sediment sinks provide favourable soil conditions, owing to their higher infiltration and water retention capacity, better aggregation, and increased nutrient availability [e.g., *Imeson et al.*, 1996]; the corresponding source areas represent active erosion and transport zones with low organic carbon concentrations [*J Hill and Schütt*, 2000].

Probably most operational imaging spectroscopy surveys have been performed to assess soil contamination caused by chronic or accidental pollution from metal mining. Following studies in the US, e.g., *Swayze et al.* [1996], the MINEO project [*Chevrel et al.*, 2003] investigated five mining areas in Europe using HyMap airborne imaging spectrometer data. Imaging spectrometry was used to map the extent and type of chronicle heavy metal contamination based on pyrite oxidation trace minerals. These indicators were used to assess the environmental impact of historical mining sites on soil contamination, and for remediation planning.

In the event of a collapsed dam for mine tailings in southern Spain in 1999 the heavy metal contamination of soils was explored using *HyMAP* imaging spectroscopy data (Fig. 18). Based on chemical and spectroscopy analysis of soil samples, prediction of heavy metals (As, Cd, Cu, Fe, Hg, Pb, S, Sb, and Zn) was achieved by stepwise MLR analysis and an artificial neural network approach. It was possible to predict six out of nine elements with high accuracy, using this approach. The best coefficients of determination (R^2) between the predicted and chemically analysed concentrations were As, 0.84; Fe, 0.72; Hg, 0.96; Pb, 0.95; S, 0.87; and Sb, 0.93, respectively. Results for Cd (0.51), Cu (0.43), and Zn (0.24) were not significant [*Kemper and Sommer*, 2002]. In addition to the PS analysis, a Variable Multiple Endmember Spectral Mixture Analysis (VMESMA, [*García-Haro et al.*, 2005]) was used to estimate the sludge abundance derived from the HyMap data. Furthermore, the analysis of residual pyrite-bearing material could be used to assess acidification risk and the distribution of residual heavy metal contamination. This assessment was based on an artificial mixture experiment and derived simple stoichiometric relationships. As a result, the spatial sludge abundance distribution and associated heavy metals could be used to assess the acidification potential and to plan counteracting remediation measures [*Kemper and Sommer*, 2002].

In summary, it can be concluded that the reflectance properties of soils enable the assessment of various contaminants in their environment and that imaging spectroscopy technology proved to be promising for that purpose.

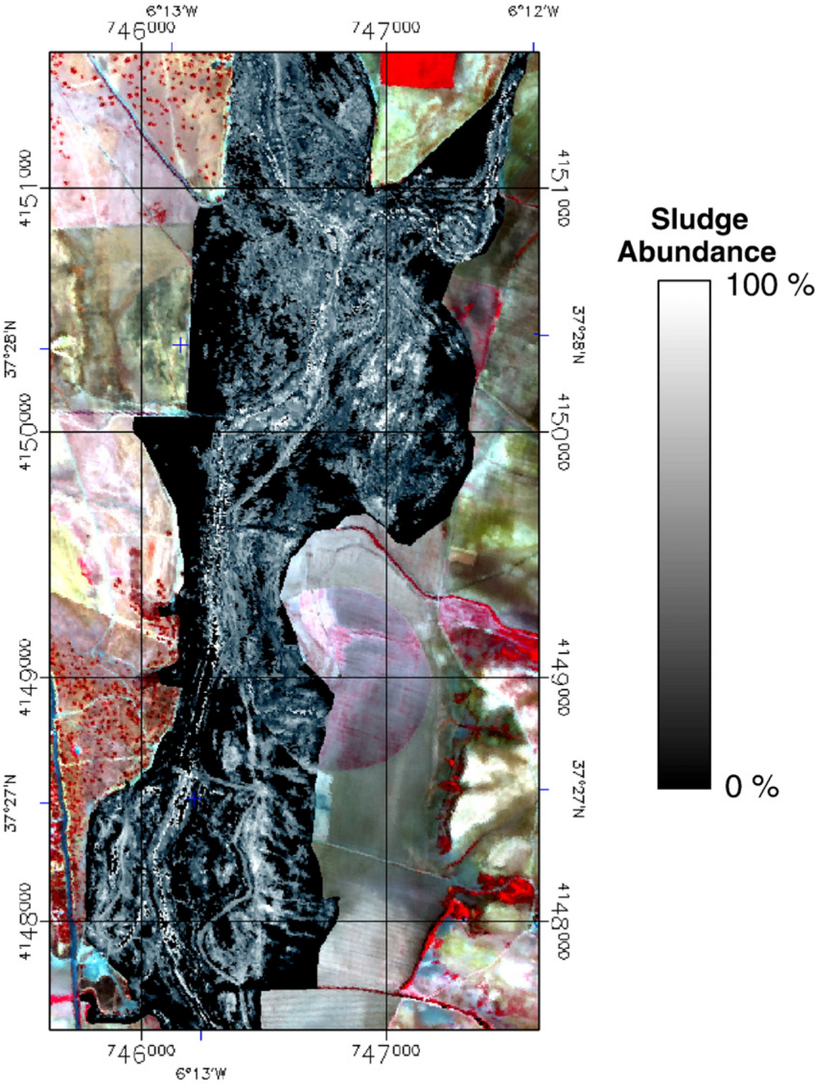

Fig. 18. Sludge abundance map based on HyMap data from 1999 in Aznalcollar, Spain. The sludge-affected area (black background) is superimposed on the HyMap false color image [after *Kemper and Sommer*, 2003].

3.3.9 Soil proxies

The efficiency of using RS to map soil properties in densely vegetated areas depends on indirect relations between vegetation and soil attributes. As already outlined in the introduction, vegetation indices and time series can be used to delineate soil patterns. Yet, more detailed information on the vegetation cover is needed for retrieving soil properties. Two useful but prospective proxy indicators have been used to obtain soil property information from RS: Plant Functional Types (PFT) and Ellenberg indicator values [*Mulder et al.*, 2011].

A central tenet in the concept of PFT is that morphological and physiological adaptations are linked in predictable ways by resource limitations, responses to disturbance, biotic factors or other aspects of the environment. The extent to which such linkages are generalized will determine the ability to detect functional types with remote sensing [*Ustin and Gamon*, 2010]. For example, abiotic factors that affect biodiversity are the nutrients available, such as nitrogen, and the prevailing climatic conditions. In some cases, low levels of nutrients lead to high levels of biodiversity [*Forde et al.*, 2008]. *Diekmann* [2003] shows that the relation between nutrient requirements of plants and nutrient availability in soils can be used to derive soil attributes. Accordingly, the concept of PFT can be used to derive the specific type or group of species that grow on typical soils. *Schaepman et al.* [2007] showed that PFT may be derived from high resolution imaging spectrometer data on a plot level. *Sun et al.* [2008] developed the current global *MODIS* PFT product, which is a map with the distribution and abundance of major PFT. *Ustin and Gamon* [2010] proposed the new concept of 'optical' types. They argue that functional types can be distinguished largely on the basis of optical properties detectable by remote sensing. To fully utilize the potential of remote sensing, data must be combined with ecological models linking structural, physiological and phenological traits based on resource constraints. See *Ustin and Gamon* [2010] for an overview of different sensors and their implications for assessing PFT. Hence, PFT regulate or are regulated by ecosystem processes and have discrete different functions within the ecosystems [*Mulder et al.*, 2011].

For the same reasons as the PFT, Ellenberg indicator values can be used to retrieve soil attributes. Originally, the Ellenberg indicator values were calculated for flora mapped on the basis of intensive fieldwork [*Ellenberg*, 1988]. However, *Schmidtlein* [2005]showed that imaging spectroscopy can be used as a tool for mapping Ellenberg indicator values for soil water content, soil pH and soil fertility. The Ellenberg indicator values scale the flora of a region along gradients reflecting light, temperature, moisture, soil pH, fertility and salinity. This way, the flora can be used to monitor environmental change and thereby changes in the soil [*Diekmann*, 2003; *M O Hill et al.*, 2000].

4 Bridging the gap: opportunities and limitations

4.1 Remote sensing technologies

Over the past decades, major technological and analytical advances have been made in various RS fields and disciplines. PS has been successfully used to derive quantitative and qualitative soil information [*Viscarra Rossel et al.*, 2006b]. Most reported studies demonstrated the high potential of PS to estimate soil properties, based on clear absorption features, at the laboratory and local scale [*Ben-Dor et al.*, 2008]. However, for large-scale mapping of soil properties methods need to be extended beyond the plot scale. Various soil properties are difficult to characterize using spectroscopy due to the lack of diagnostic absorption features and complex scattering behaviour within the soil mixture [*Clark and Roush*, 1984]. Quantification and qualification of such soil properties require methods that model the complex scattering behaviour of soils [*Clark et al.*, 2003]. For that, the sample preparation, spectral measurements, data analysis and model parameterization require special expertise [*Pompilio et al.*, 2010]. Currently, these methods are not yet fully operational, but will become available in the near future.

Important qualitative and, to a lesser extent, quantitative soil information can be obtained from RS data. Airborne and spaceborne RS provide qualitative information on soil properties, having clear diagnostic absorption features, at a regional to global scale. However, compared to PS, RS-derived information has a lower accuracy and feasibility to obtain information compared to proximal sensing (Table 3). The main limiting factors are (1) the coarse spatial and spectral resolution, (2) the low signal-to-noise ratio of high-resolution RS data and (3) the bands of multispectral satellite sensors have not been positioned at diagnostic wavelengths.

Improvements in regional-scale DSM result from the integrated use of RS and PS with geostatistical methods. In every step of the soil mapping process, spectroscopy can play a key role and can deliver data in a time and cost efficient manner. Although existing methods have demonstrated the value of spectral data in DSM, *Mulder* [2013] stressed that methods need the support of geostatistics and ground truth data in order to advance models for regional-scale DSM. *Mulder* [2013] further underlined the added value of advanced proximal and remote sensing combined with geostatistical methods to obtain soil information. Various studies revealed the abilities, opportunities and prospects of integrated RS data to map soil properties at regional scale [*Mulder et al.*, 2011]. One of the best examples includes the *ASTER* Geoscience product [*Cudahy*, 2012] and the mineral maps that were made for Australia [*Lau et al.*, 2012]. However, there is a strong need for sophisticated methods to analyse and integrate large-datasets [*Mulder et al.*, 2013a]. Furthermore, spectral band configurations (spectral resolution and the position of the sensors' bands) of multispectral satellites can be optimized for soil parameter retrieval to enable more comprehensive soil monitoring. Although the recently launched *Landsat 8* satellite and the upcoming *Sentinel-2* satellites represent further technological improvements in the optical multispectral, their band configurations serve multiple purposes and are not specifically adjusted to diagnostic soil absorption and reflection features.

Although much progress has been made, current PS methods are not readily implemented at spaceborne level. There are, however, space-based instruments that partially support such approaches [*Pieters et al.*, 2009] or will be available in the future [*Stuffler et al.*, 2009]. The spectral band settings and improved signal-to-noise performance of upcoming spectrometers in space will certainly improve the retrievals of soil-based information using advanced spectral mixing approaches. Secondly, most methods used for retrieving soil attributes have been developed using local or regional correlation approaches, and may not scale for operational use over vast areas. Considering the use of RS for large-scale DSM, research is needed on extending current methods beyond the plot. Indications are that perspectives exist to develop methods for large-scale mapping, as indicated in *Iwahashi and Pike* [2007], *Ballantine et al.* [2005], *Wagner et al.* [2007] and *Ninomiya et al.* [2005]. Thirdly, although experiments retrieving soil information work well when using PS, their accuracy drops when (larger-scale) RS methods are being used. This accuracy drop is mainly caused by sensor noise [*Phillips et al.*, 2009], directional reflectance [*Kriebel*, 1978], topographic [*Richter and Schläpfer*, 2002] atmospheric distortions [*Gail et al.*, 1994; *Richter and Schläpfer*, 2002], and increased mixture of soil properties. Because advances in PS have evolved much faster as compared to RS, a technology gap still has to be bridged.

Table 2: Remote sensing technologies used for soil attribute retrieval [modifed after *Mulder et al.*, 2011].

Remote sensing technologies	Sensor type	Spectral bands	Spectral class	Spectral range (µm)	Spatial resolution (m)	Revisit time (days)	Spatial coverage	SCORPAN factors	Approximate data costs ($)
Optical									
Spaceborne									
Landsat	MS	11	VNIR - TIR	0.43 - 12.51	15 - 60	16	Global	S, O, P, N	0
MODIS	MS	36	VNIR - TIR	0.40 - 14.40	250 - 1000	1	Global	S, O, P	0
MERIS	MS	15	VNIR	0.39 - 1.40	300	3	Global	S, O, P	0
ASTER	MS	15	VNIR - TIR	0.52 - 11.65	15 - 90	16	Global	S, O, R, P, N	80/scene
Hyperion	IS	242	VNIR - SWIR	0.40 - 2.50	30	irregular	Regional	S, O, P, N	0
ALOS/PRISM	MS	1	VIS	0.52 - 0.77	2.5	46	Local	R, N	600/scene
Sentinel-2	MS	13	VNIR - SWIR	0.44 - 2.19	10 - 60	5 - 10	Global	S, O, P, N	0
Airborne									
AVISIRS	IS	224	VNIR - SWIR	0.38 - 2.50	4 - 20	irregular	Local	S, O, R, P, N	> 20'000/survey
HyMAP	IS	128	VNIR - SWIR	0.45 - 2.48	2 - 10	irregular	Local	S, O, R, P, N	> 20'000/survey
APEX	IS	300	VNIR - SWIR	0.40 - 2.50	2 - 5	irregular	Local	S, O, R, P, N	> 20'000/survey
DAIS-7915	IS	79	VNIR - TIR	0.45 - 12.00	3 - 10	irregular	Local	S, O, R, P, N	> 20'000/survey
LiDAR									
Spaceborne									
ICEsat GLAS	Active	2	VNIR	0.53, 1.06	70	91	Global	R	0
Airborne									
ALTM Germini	Active	1	NIR	1.06	2 - 3.5	irregular	Local	R, N	> 20'000/survey
ALTM Orion	Active	1	NIR	1.06	< 1.5	irregular	Local	R, N	> 20'000/survey
RADAR				(cm)					
Spaceborne									
SRTM	Active	2	C, X	2.5 - 8.0	30	none	Global	R	0
RADARSAT2	Active	1	C	2.5 - 4.0	3 - 100	24	Global	S, R	8000/scene
ASAR Envisat	Active	1	C	2.5 - 4.0	30-1000	35	Global	S	0
PALSAR	Active	1	L	15 - 30	100	46	Global	S	0
SMOS	Passive	1	L	15 - 30	50000	3	Global	S	0
SMAP	Act./Pas.	1	L	15 - 30		2 - 3	Global	S	0
Sentinel-1	Active	1	C	2.5 - 4.0	1000	3 - 6	Global	S, R	0
Airborne									
E-SAR	Active	4	X, C, L, P	2.5 - 85	2-4	irregular	Local	S, R	> 20'000/survey
GeoSAR	Active	2	X, P	2.5 - 85	3	irregular	Local	S, R	> 20'000/survey
MIRAMAP	Active	3	X, C, L	2.5 - 30	5-50	irregular	Local	S, R	> 20'000/survey

Optical sensor types distinguish between multispectral (MS) sensors and imaging spectroscopy (IS) sensors. Spectral classes distinguish between visible near-infrared (VNIR), shortwave infrared (SWIR), thermal infrared (TIR) and different radar bands (X, C, L, P). Spatial coverage distinguishes local = $<10^4$, regional = $>10^4$ - $<10^7$, and global = $>10^7$ scales. SCORPAN factors comprise soil (S), organisms (O), topography (R), lithology (P), and spatial position (N).

4.2 Remote sensing products

Reported DSM-studies made limited use of the various methods that are available for spectroscopy and geostatistics [*Ben-Dor et al.*, 2009; *Dewitte et al.*, 2012]. It was found that current research using RS data typically produced qualitative outputs. Also, the overall model accuracy reduced with increasing scale of the study area. This was contributed to incompatibility between the RS data and the available sample data. From the viewpoint of the soil scientists, the major gap is the lack of readily available RS-based soil products. Currently, soil scientists generate their own input data for their models. However, they may be limited in their knowledge of RS and PS tools and methods. Here, communication is the limiting factor, which is needed to initiate a multidisciplinary approach for soil mapping [*Mulder*, 2013].

Despite the large potential of using RS and PS methods for DSM [*Ben-Dor et al.*, 2009; *Mulder et al.*, 2011], advances are deemed necessary to fully develop large-scale methodologies. Advances may be expected in developing more quantitative methods and enhanced geostatistical analysis using RS and PS data by making use of recent developments in DSM-related disciplines. Alternatively to the DSM approach, imaging spectroscopy has been used to map e.g. soil mineralogy. Recent studies [*van der Meer et al.*, 2012] demonstrated that, at the moment, RS data does not provide the high spectral resolution that is needed to quantitatively map soil mineralogy. The physical nature of minerals is too complex [*Clark*, 1999] to be modelled in a quantitative way using imaging spectroscopy alone. The use of a geostatistical approach in combination with a small representative sample substantially improves the feasibility to quantitatively map mineralogy [*Mulder et al.*, 2013b].

The soil spectroscopy community has not yet explored spectral deconvolution for assessing soil properties using PS other than mineralogy and soil moisture [*Whiting et al.*, 2004]. Various methods for estimating properties of the topsoil using PS were found to be sufficiently accurate compared to chemical soil analysis. The remaining inaccuracies in estimated soil properties of the topsoil, such as soil organic matter, have often been contributed to other constituents in soil samples [*Bartholomeus et al.*, 2008]. This implies actually, that the inaccuracies are a consequence of overlapping absorption features, which need to be accounted for in detailed analysis [*Mulder*, 2013].

Additional aspects of DSM that deserve further attention in the development of soil products are: (1) the interpolation of gaps in the spatial coverage due to cloud cover, vegetation or other obscuring areas; (2) the combination of PS and RS data with geostatistics to address the lack of soil property data at regional to global scales; and (3) the improved understanding and multi-temporal monitoring of processes related to soil property changes to model future variations. The soil science community is aware of these challenges and current efforts are on data harmonization [*GlobalSoilPartnership*, 2011; *Panagos et al.*, 2011; *Sulaeman et al.*, 2012] while research efforts are initiated for temporal modelling of soil properties [*Banwart*, 2011]. Despite these initiatives, it is expected that the existing soil data have insufficient coverage and thematic variability for regional and global models. The time and cost associated with collecting sufficient data are comprehensive. Therefore, it is important to develop new methods, for the benefit of various research disciplines focussing on modelling environmental changes, climate change adaptation, food security and soil services [*Mulder*, 2013].

Table 3: Remote sensing products for soil and terrain attributes [modifed after *Mulder et al.*, 2011].

Soil and terrain attributes	RADAR		LiDAR	Optical		Sensor class	Methods
	Passiv	Active		MS	IS		
Soil attributes							
Mineralogy	-	-	-	3	4	RS	Quartz-, Carbonate-, Mafic Index, SAM, PPI, SMA, MESMA, VMESMA, SSEE, SPA
Soil texture	-	3	-	3	3	RS/PS	Merged Radar and spectral data, Band ratios, Matched filtering algorithms, Clay index, MLR, PLSR
Iron content	-	-	-	1	3	RS/PS	PCA, Redness Index, Soil color, Constrained Energy Minimization, Continuum removal
Soil organic carbon	-	-	-	1	5	RS/PS	SOC indices, Multivariate regression modelling, PLSR
Soil moisture	4	4	-	3	2	RS/PS	Soil water index, Surface energy balance models, Soil line technique, MLR of absorption dip
Soil salinity	-	-	-	2	3	RS/PS	Characterization by salt scalds, halophytic vegetation, SAR C-,P- and L-bands, (normalized) Salinity index, Matched filtering, Multivariate regression and VNIR signatures
Carbonate content	-	-	-	2	2	RS/PS	Calcite index, Continuum removal
Vegetation patterns	-	-	-	5	5	RS	Vegetation indices (e.g. NDVI, EVI, SAVI), Biogeographical ordination, Spectral unmixing
Land cover	-	2	-	4	5	RS	(un)supervised Classification, Spectral unmixing
Land degradation	-	2	-	5	5	RS	Multivariate pettern recognition algorithms, MESMA, spectral continuum analysis
Terrain attributes							
Elevation	-	5	5	3	-	RS	Summary statistics
Slope	-	5	5	3	-	RS	Directional derivatives
Aspect	-	5	5	3	-	RS	Directional derivatives
Dissection	-	4	4	2	-	RS	Directional derivatives DEM
Landform unit	-	4	4	4	2	RS	Automated classification, DEM, Fuzzy classification, Object-based classification, Expert driven multi-level approach, Topographic Position Index
Digital soil mapping	-	5	4	4	3	RS	Ordinary kriging, co-kriging, (generalized) linear models, regression analysis
Soil type	-	-	-	3	5	RS/PS	Plant functional type, Ellenberg's indicator values, NDVI

Numbers (1–5) indicate the feasibility to determine soil and terrain attributes with remote and proximal sensing instruments. The feasibility represents the weighted average of scores for the number of studies reported, dataset quality, obtained result and applicability to field surveys. 1=low, 2=low-medium, 3=medium, 4=medium-high and 5=high [*Mulder et al.*, 2011].

4.3 Future directions and soil products

4.3.1 Research foci and products for DSM

For future research in soil science, it is important to develop methods that allow modelling of a wide set of soil properties. Considering the need of soil information for regional and global-scale environmental models, spatiotemporal modelling is the future of soil mapping [*Heuvelink and Webster*, 2001; *Katzfuss and Cressie*, 2012]. To develop and advance such spatiotemporal models, RS and PS with geostatistics will play the key role. Integration of legacy, laboratory, soil profile data, field and airborne or satellite data with modelling approaches will allow to accurately monitor changes in soil, vegetation and their feedbacks [*Milcu et al.*, 2012], over various spatial and temporal scales. Furthermore, large-scale subsurface information is needed, based on technologies like gamma-ray spectroscopy [*Wilford et al.*, 1997], radar [*Merlin et al.*, 2013] or electric conductivity [*Lambot et al.*, 2004], to complement data from sensors extracting soil surface information. Another remaining challenge is the development of more quantitative geostatistical approaches for large datasets [*Katzfuss*, 2011; 2013]. Such methods are transferrable to different landscapes and may deliver more accurate and comprehensive information about soils, soil resources and soil ecosystem services [*Mulder*, 2013].

With respect to DSM, numerous studies provide evidence that soil taxonomic data and soil properties can be predicted successfully using sets of environmental covariates, as shown in various soil-landscape settings [e.g., *Grunwald*, 2009; *Hartemink and McBratney*, 2008; *Lagacherie et al.*, 2007] (Fig. 19). The trend to formalize pedological expertise in form of quantitative soil prediction models of various types is ongoing.

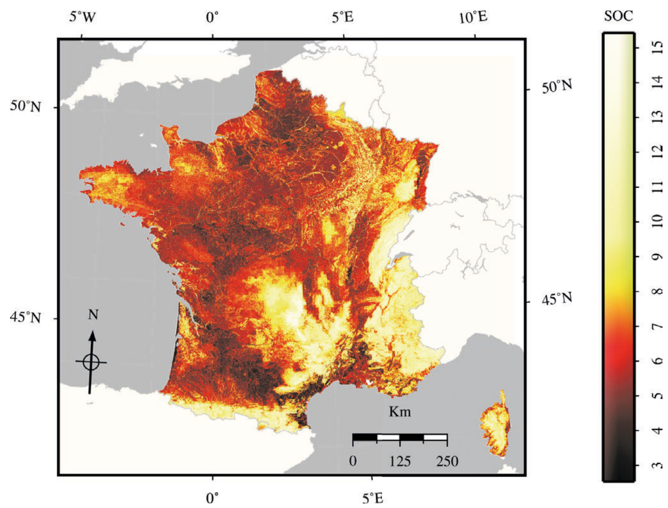

Fig. 19. Spatial distribution of soil organic carbon stocks (kg/m^2), at the national scale (France) [after *Martin et al.*, 2014].

An interesting and contemporary research topic involves the development of a methodology for quantitative extrapolation of soil information across the globe, also referred to as the Homosoil method. This method assumes homology of soil-forming factors between a reference area, having good legacy data, and a region of interest where soil information is sparse. Hence, the rules calibrated in the reference area may be applied elsewhere, realising its limitations and extrapolation consequences [*Mallavan et al.*, 2010]. Global RS products are key for establishing a framework in which the homology of soil-forming factors between areas can be established. Within this context, finite mixture modelling approaches have been successful in deriving specific systems in which soils develop [*Mulder et al.*, 2014]. Another important research topic in DSM concerns digital soil assessment, which comprises three main processes: (1) soil attribute space inference, (2) evaluation of soil functions and the threats to soils, and (3) risk assessment and the development of strategies for soil protection [*Carré et al.*, 2007]. Digital soil risk assessment consists of integrating political, social, economical parameters and general environmental threats for building, modelling and testing scenarios about environmental perspectives. This path responds to the pressing environmental issues requiring accurate and high-resolution, spatially-explicit soil data to conduct a holistic assessment of soil-environmental systems.

Future challenges will entail to apply DSM to various soil-landscape settings accounting for spatial as well as temporal soil variability. Digital soil mapping will need to encompass three-dimensional soil bodies across landscapes [*Lacoste et al.*, 2014]. So far, DSM has focused on the topsoil but mapping of soil characteristics in the subsurface are critical to address, e.g. nutrient enrichment and pollution problems, carbon sequestration. Bridging the gap between research and operational DSM programs will require fusing of expert-knowledge from soil surveyors and research scientists. Despite technological and methodological advancements in DSM, it will be critical to collect reconnaissance soil data without relying too much on legacy soil data. Fusing of soil and environmental covariates and development of multi-sensor systems will be important to advance and homogenize future DSM.

Future DSM products: GlobalSoilMap

In 2008, a global consortium (GlobalSoilMap) has been formed that aims to make a new digital soil map of the world using state-of-the-art and emerging technologies for soil mapping and predicting soil properties at fine resolution. This new global soil map aims to predict primary functional soil properties that define soil depth, water storage, texture, fertility and carbon at fine spatial resolution (~100 m) for most of the ice-free land surface of the globe over the next five years. These maps will be supplemented by interpretation and functionality options to support improved decisions for a range of global issues such as food production, climate change, and environmental degradation [*Arrouays et al.*, 2014]. GlobalSoilMap will be freely available, web-accessible, and widely distributed.

4.3.2 Remote sensing - data availability, products and services

In addition to the existing earth observation satellites, newly developed products and sensors will provide data for the soil science community; the new WorldDEM of the *TanDEM-X* mission will improve global terrain analysis. The upcoming *Sentinels* and the

SMAP mission will enable advanced analysis of soil moisture. Furthermore, the planned imaging spectroscopy mission *EnMAP* (planned launch in 2017) aims to provide high quality data for global environmental monitoring, including soil status and properties. On-going multi-sensor and multi-scale approaches offer great potential for soil system monitoring over large spatial extents and can contribute to a more precise spatial assessment of soil properties. Furthermore, novel designs in senor technology enable multiple view angle observations to better account for anisotropic reflectance from soil surfaces.

Copernicus services

The Copernicus programme comprises satellite-borne earth observation and in-situ data, and a services component that combines these in order to provide information essential for monitoring the terrestrial environment. The Copernicus land monitoring service provides geographical information on land cover/land use and on variables related to vegetation state and the water cycle. With respect to the pre-operational state of the *Sentinel* missions, the only soil related product is the Soil Water Index (subsection 3.3.3). In the near future, the launched and upcoming *Sentinel-1* satellites will enable the operational monitoring of surface soil moisture at 1 km spatial resolution [*Gruber et al.*, 2013].

THEIA Land Data Centre

The THEIA Land Data Centre is a French inter-agency initiative designed to promote the use of satellite data for (1) environmental research on land surfaces, (2) public policy monitoring and (3) management of environmental resources. THEIA aims fostering the use of remote sensing data to measure the impact of human pressure and climate on various scales, focusing on both natural and anthropological research [*Hagolle*, 2014]. Within the Land Data Centre, the National Centre of Space Research (CNES) is setting up a production center named MUSCATE, and already exists in the form of a prototype. This center will provide users with ready-to-use products derived from time-series of images acquired over large areas. Here, Sentinel-2 will be the spearhead of the production center, but currently, MUSCATE produces data from the SPOT4 (Take 5) experiment and is processing all Landsat data acquired over mainland France from 2009 to 2011.

LP DAAC

NASA and USGS process, archive and distribute Land Processes data, received from EOS satellites, thus establishing a Distributed Active Archive Center, or LP DAAC. The LP DAAC is a component of NASA's Earth Observing System (EOS) Data and Information System (EOSDIS). LP DAAC processes, archives, and distributes land data and products derived from the EOS sensors. The LP DAAC handles data from three EOS instruments aboard two operational satellite platforms: ASTER and MODIS from Terra, and MODIS from Aqua. ASTER data and MODIS land products are received, processed, distributed, and archived. Both data sets are main contributors to the inter-disciplinary study of the integrated Earth system. Furthermore, the USGS EarthExplorer (EE) tool provides users access to the satellite images, aerial photographs, and cartographic products from several sources [*USGS*, 2014].

5 Conclusions and recommendations

This report summarizes and reviews the use of remote and proximal sensing for soil survey. In summary, remote sensing provides data (1) supporting the segmentation of the landscape into rather homogeneous soil-landscape units whose soil composition can be determined by sampling or that can be used as a source of secondary information, (2) allowing measurement or prediction of soil properties by means of physically-based and empirical methods, and (3) supporting spatial interpolation of sparsely sampled soil property data as a primary or secondary data source [*Mulder*, 2013]. Table 2 gives an overview of the various remote sensing technologies used for soil assessments complemented by Table 3 highlighting remote sensing products for soil properties as discussed in this report.

A wide variety of soil attributes have been derived with use of statistical and chemometric analysis of spectroscopic data [*Minasny and McBratney*, 2008; *Viscarra Rossel and McBratney*, 2008], which can be used for DSM [*Minasny et al.*, 2009]. However, as can be seen in Table 3, the feasibility to derive these soil attributes is on average 'medium', which means that current methods are not fully developed yet. The retrieval of soil attributes with remote sensing has made progress, particularly since the launch of advanced multispectral sensors and imaging spectrometers such as *ASTER* and *Hyperion*, which have made it possible to detect subtle differences between spectral signatures. Various indices, proxies, quantities and patterns have been derived from remote sensing in order to map soil and terrain attributes. However, remote sensing technology still needs to catch up with proximal sensing in terms of number and feasibility of derived soil attributes. Due to the heterogeneity of landscapes and the spatial resolution of the imagery (Table 2) it is often difficult to find pure pixels representing soil or bare rock. Advanced unmixing tool methods, such as Tetracorder [*Clark et al.*, 2003] and PRISM [*Kokaly*, 2011], are needed to extract sub-pixel soil and rock composition. Finally, the spatial extent of most reported work is still restricted to local studies and needs to be expanded to allow for regional soil assessments.

Remote sensing data is used in DSM as covariates for the prediction of soil classes or soil properties. In general, the use of spectral imagery for the spatial prediction of soil properties is based on the spatial relation between existing soil data and observed patterns in the imagery, and not on physically-based retrievals, such as soil moisture [*Dobos et al.*, 2000; *Stoorvogel et al.*, 2009]. Over the last years, spectral proximal sensing showed to be useful as part of DSM [*Minasny et al.*, 2009; *Viscarra Rossel and McBratney*, 2008]. Dependent on spatial and spectral resolution, spatial coverage and the availability of legacy data, remote and proximal sensing data are either used as primary or secondary data source for the spatial prediction of soil properties. In vegetated areas soil proxies, such as NDVI, plant functional type or Ellenberg indicator values, have been used to derive soil properties, but with mixed success. Alternatively, data mining techniques such as classification trees – which are generated from a matrix of environmental variables – have been used to estimate soil properties and to create soil maps [*Bourennane et al.*, 2014; *Martin et al.*, 2014; *Saby et al.*, 2009].

Bridging the technology gap between proximal and remote sensing, future work will focus on the improved integration of remote and proximal sensing using scaling-based approaches in order to make optimal use of all data sources available. Revisit time or temporal approaches are still limited by satellite orbital constraints and/or data download capacity. Soil moisture based retrievals have become increasingly feasible with the launch of *SMOS* (Soil Moisture Ocean Salinity), but its spatial resolution is still too coarse for soil plot-size retrievals. Here, the recently launched *Sentinel-1* mission is expected to provide soil moisture data in a high spatial and temporal resolution. Certainly, the planned availability of *SMAP* will further contribute to improved retrievals, including freeze/thaw status of the surface. In addition, upcoming remote sensing data of *Sentinel-2* missions and the imaging spectroscopy mission *EnMAP*, among others, will spark further opportunities to quantify and monitor various soil properties in great detail.

Future research will aim for the integrated use of remote sensing methods for spatial segmentation, as well as measurements and spatial prediction of soil properties to achieve complete area coverage. In-situ or proximal sensing methods are readily available and we will be seeing future instruments launched soon supporting these methods at larger spatial scales enhancing the perspectives of DSM.

6 References

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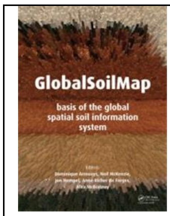
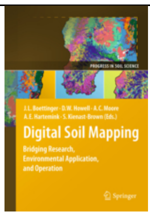
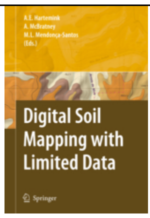
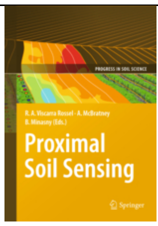
	Arrouays, A.; McKenzie, N.; Hempel, J.; Richer de Forges, A.; McBratney, A. (Eds.) GlobalSoilMap – Basis of the global spatial soil information system, 2014, 478p, CRC Press/Balkema.
	Boettinger, J.L.; Howell, D.W.; Moore, A.C.; Hartemink, A.E.; Kienast-Brown, S. (Eds.) Digital Soil Mapping, 2010, 473p. 148 illus., 99 illus. in color. http://www.springer.com/earth+sciences+and+geography/remote+sensing/book/978-90-481-8862-8
	Hartemink, Alfred E.; McBratney, Alex B.; Mendonça-Santos, Maria de Lourdes (Eds.) Digital Soil Mapping with Limited Data, 2008, XXIV, 445p. 109 illus., 55 illus. in color. http://www.springer.com/environment/soil+science/book/978-1-4020-8591-8
	Viscarra Rossel, Raphael A.; McBratney, Alex B.; Minasny, Budiman (Eds.) Proximal Soil Sensing, Series: Progress in Soil Science, 2010, XXIV, 448 p. http://www.springer.com/environment/soil+science/book/978-90-481-8858-1

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8 Digital resources

Theme	Description	Weblink
Soil data	GlobalSoilMap - A new digital soil map of the world using state-of-the-art and emerging technologies for soil mapping and predicting soil properties at fine spatial resolution.	http://www.globalsoilmap.net/
	SoilGrids1km is a collection of updatable soil property	http://www.isric.org/content/soilgrids
	e-SOTER: Regional pilot platform as EU contribution to a Global Soil Observing System	http://www.esoter.net/
	ASTER Geoscience	http://www.ga.gov.au/earth-observation/satellites-and-sensors/aster-radiometer/national-aster-maps.html
Spectral Library	USGS Spectroscopy Lab (USGS mineral database, software, etc.)	http://speclab.cr.usgs.gov/
	ASTER spectral library, a compilation of over 2400 spectra of natural and man made materials.	http://speclib.jpl.nasa.gov/
Environmental variables	MODIS remote sensing products (e.g. Land Surface Temperature,	http://modis.gsfc.nasa.gov/data/
	THEIA is a French initiative designed to promote the use of satellite data for environmental research on land surfaces	http://www.cesbio.ups-tlse.fr/multitemp/?p=213
	Global climate layers	http://www.worldclim.org/
	Tropical Rainfall Measuring Mission	http://trmm.gsfc.nasa.gov/
	Geological data	http://www.onegeology.org/home.html
	Earth's global land cover	http://due.esrin.esa.int/globcover/
	Global Inventory Modeling and Mapping Studies - global measure of normalized difference vegetation index	http://gcmd.nasa.gov/records/GCMD_GLCF_GIMMS.html
Digital Elevation Models	Shuttle Radar Topography Mission (SRTM)	http://www2.jpl.nasa.gov/srtm/

	ASTER GDEM	http://asterweb.jpl.nasa.gov/gdem.asp
	WorldDEM	http://www.astrium-geo.com/worlddem/